

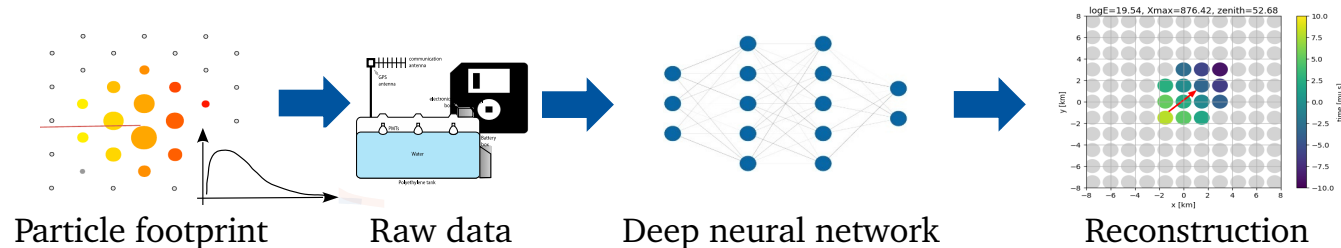
Deep Learning for UHECR Observatories

Air Shower Reconstruction at the Pierre Auger Observatory

A. Aab (Pierre Auger Collaboration) et al., JINST 16 P07019 (2021)

A. Abdul Halim (Pierre Auger Collaboration) et al., Phys. Rev. Lett. 134, 021001 (2025)

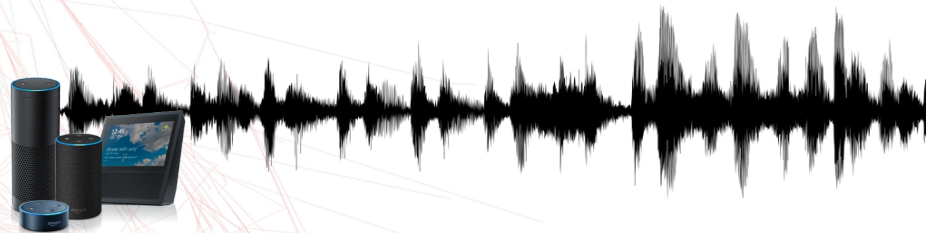
A. Abdul Halim (Pierre Auger Collaboration) et al., Phys. Rev. D 111, 022003 (2025)



Jonas Glombitza

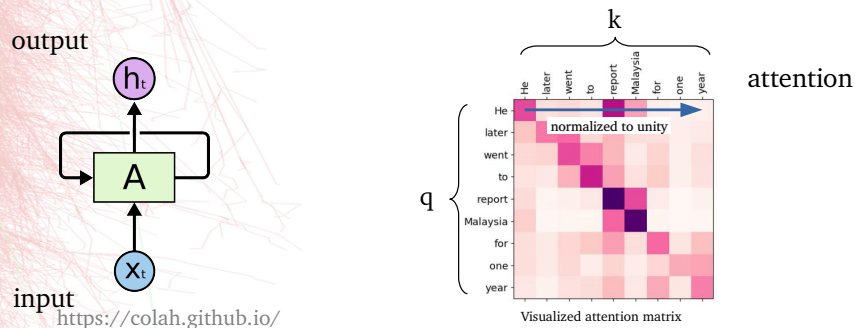
October 15, 2025

Deep Learning: RNNs & CNNs



Transformer, recurrent networks

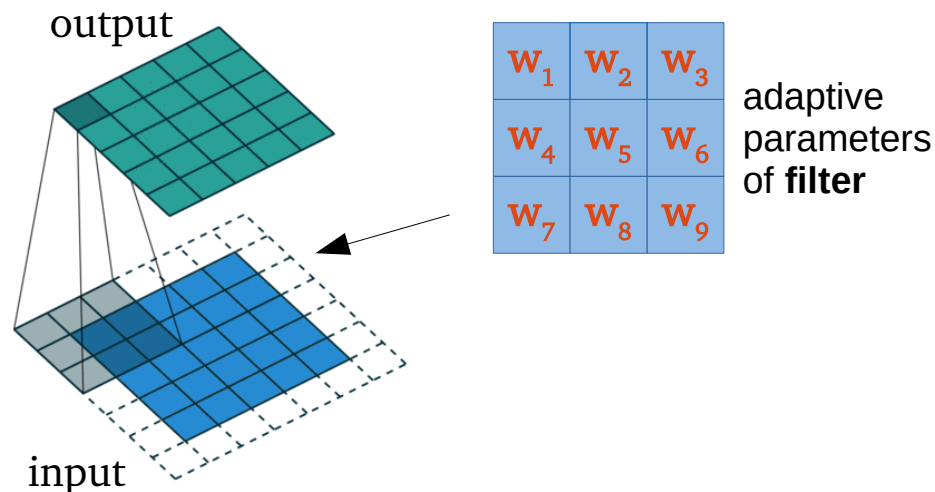
- analyze sequential data (translation)
- attention exploits pairwise relations between tokens
- no prior on locality → extract global context
- highly parallelizable (in contrast to RNNs)



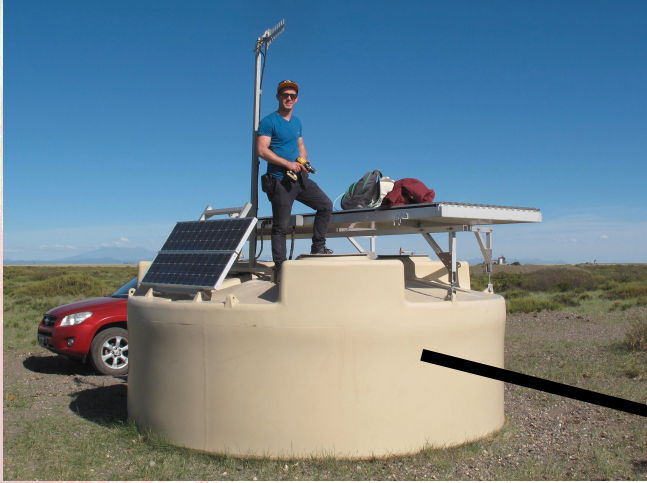
<https://colah.github.io/>

Convolutional Networks (CNNs)

- analyze image-like data
- **filter** exploits image
 - features translational invariance
 - prior on local correlations



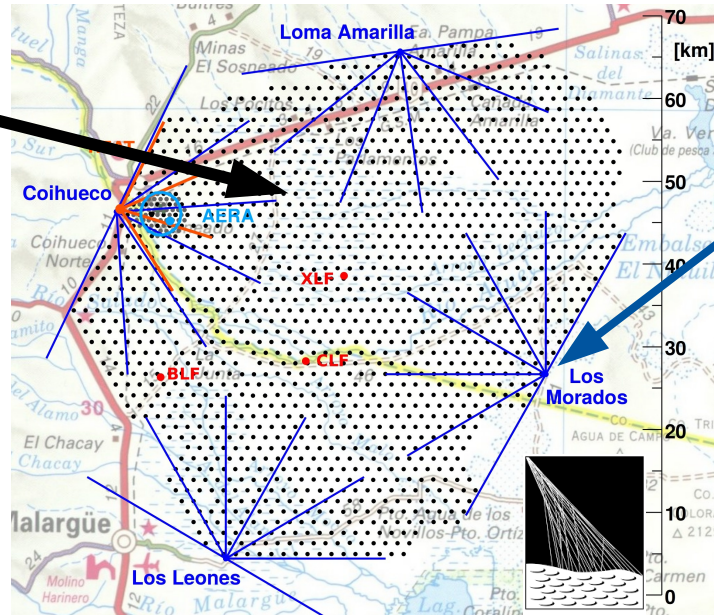
The Pierre Auger Observatory



Surface Detector (SD)

- 1660 water-Cherenkov detector stations
- 3000 km² array
- ~100% duty cycle

- largest cosmic-ray observatory
 - located in Argentina
- **hybrid** measurements



Fluorescence Detector (FD)

- 27 telescopes
- located at 4 sites
- ~15% duty cycle
(dark, moonless nights)

Deep Learning for Surface Detectors

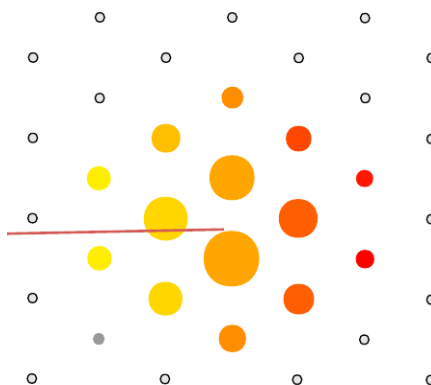
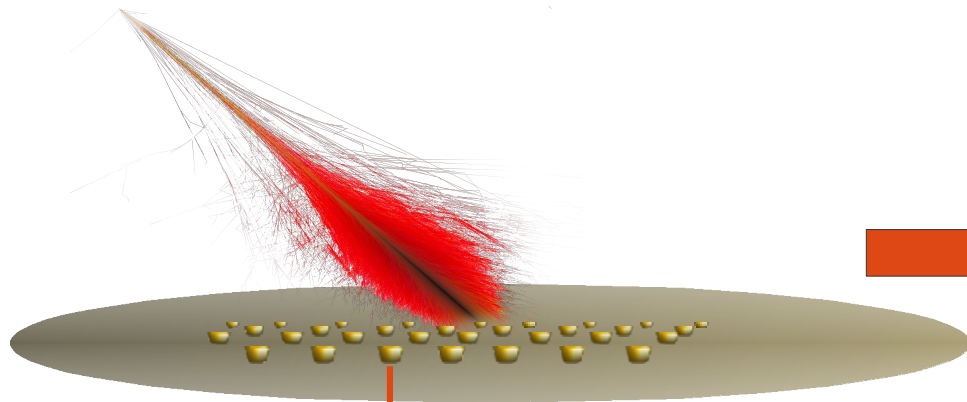
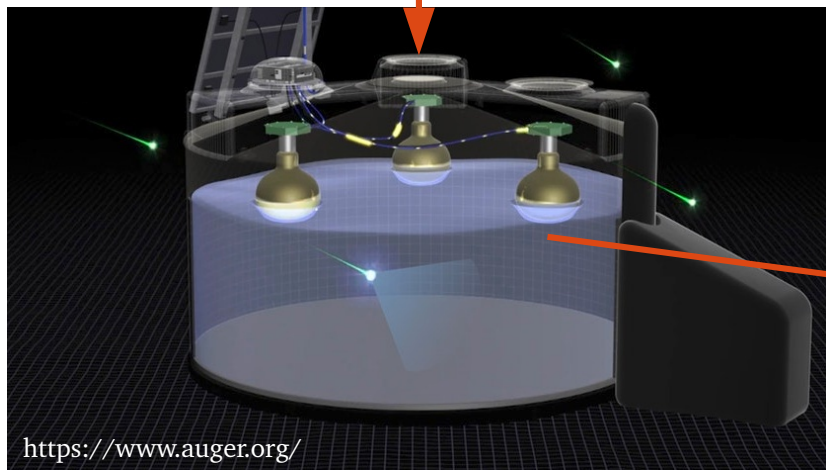
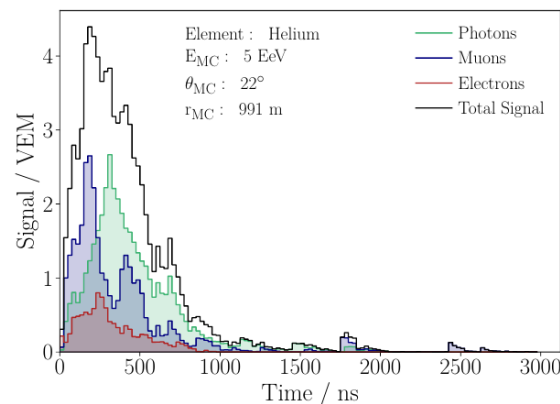


image-like
footprint



<https://www.auger.org/>



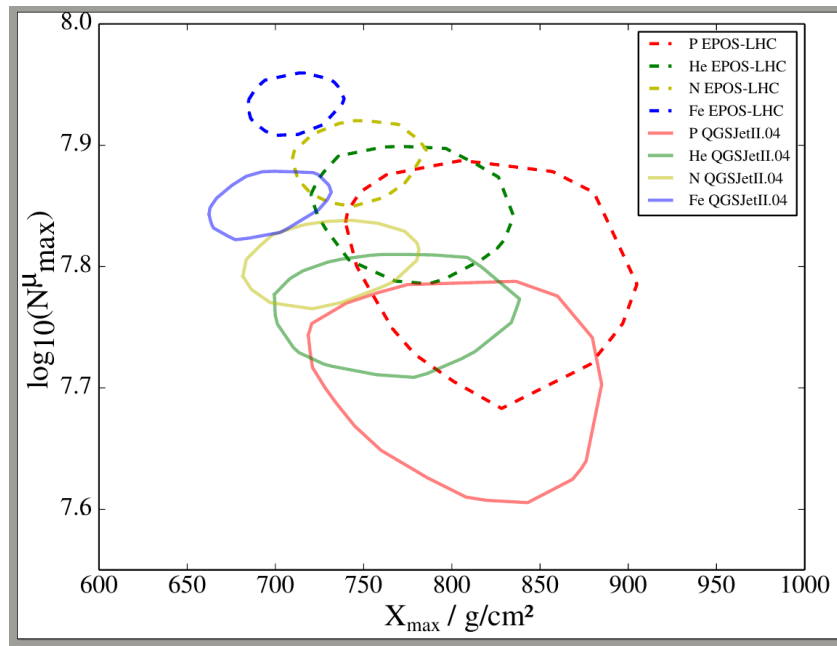
signal traces

Deep
learning!

Wasn't really
manageable before

Mass composition of UHECRs

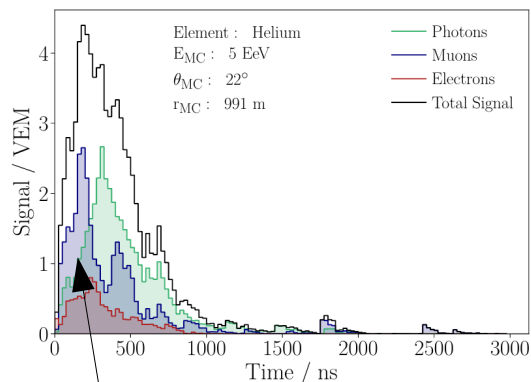
Accessible at surface
→ Surface Detector



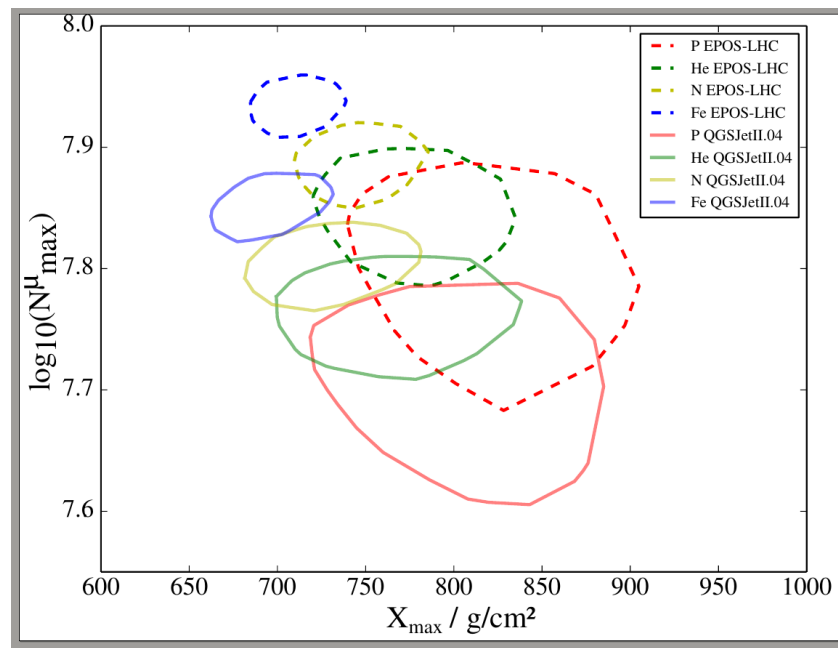
Longitudinal observation of the shower
→ Fluorescence Detector

Mass composition of UHECRs

measured SD signal trace



Accessible at surface
→ Surface Detector

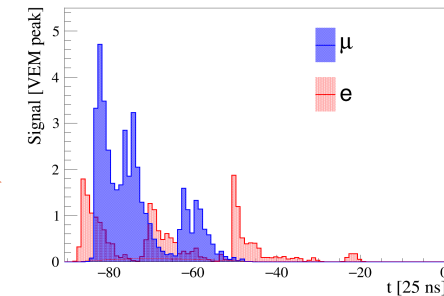
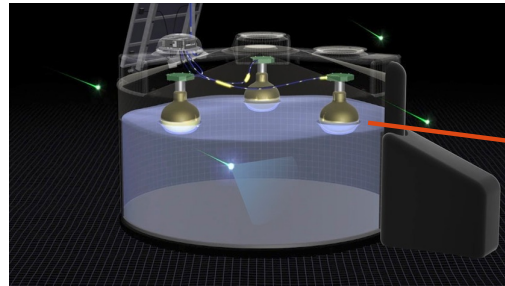


Longitudinal observation of the shower
→ Fluorescence Detector

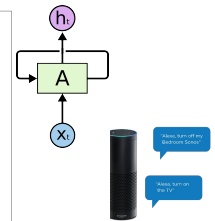
muons

→ challenging
to disentangle!

Reconstruction of the muon trace

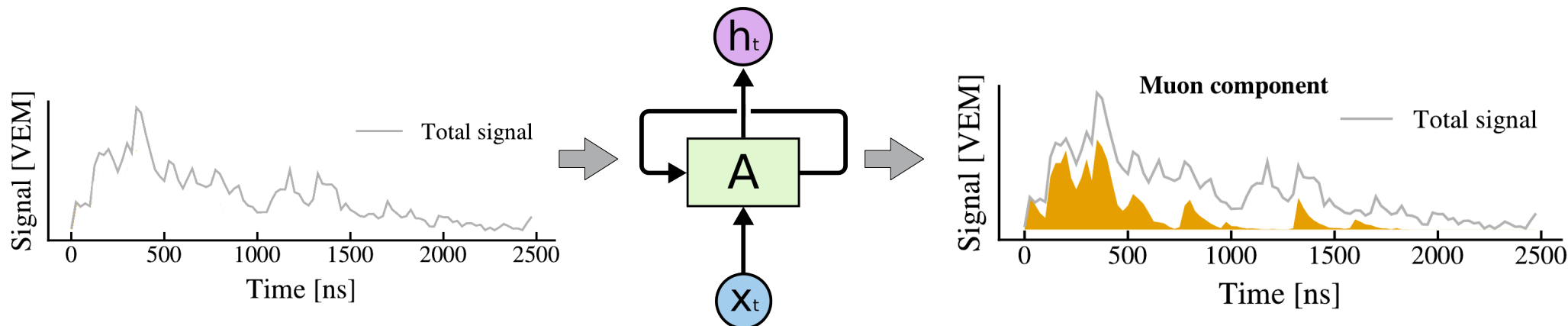


signal traces $\rightarrow$ time series (audio)



Extraction of the muon trace

- exploit signal trace of the surface detector
 - ♦ extract time-dependent muon signals → muon trace



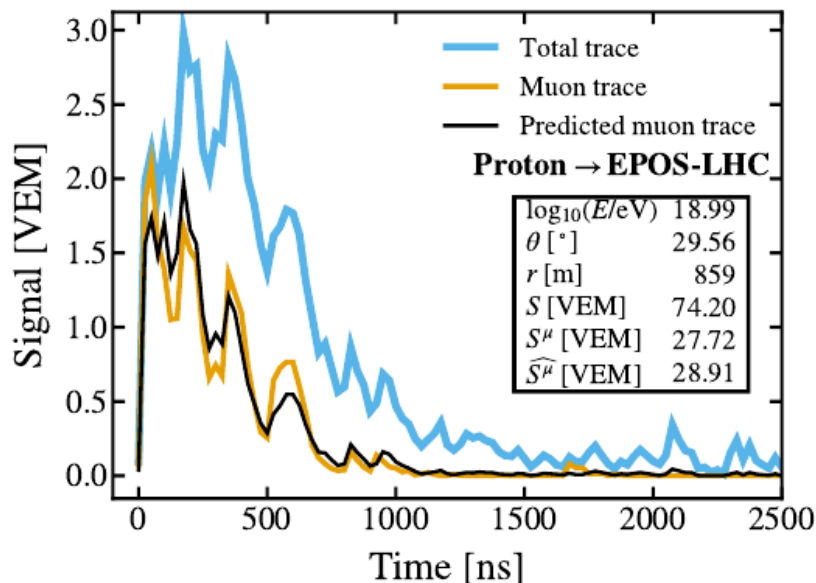
$$L = \frac{1}{200} \sum_{i=1}^{200} \left(\widehat{S^{\mu}}_i - S^{\mu}_i \right)^2.$$

prediction truth

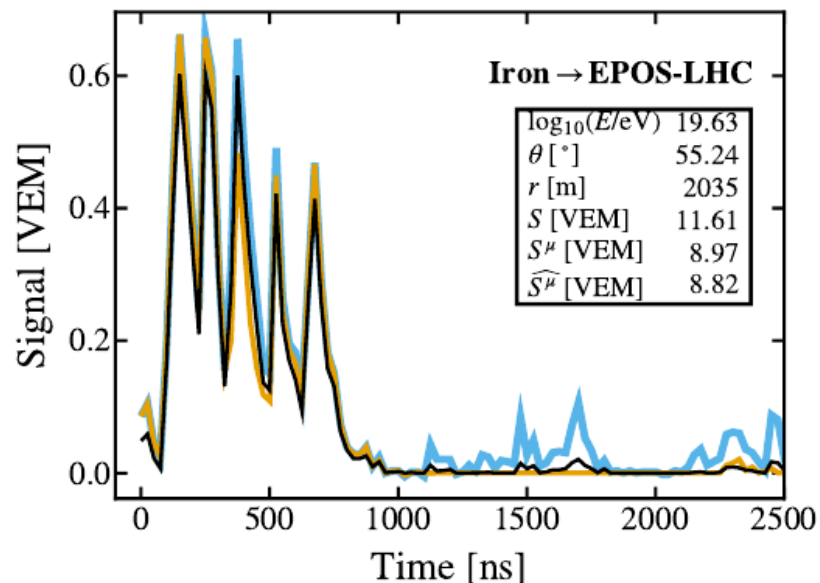
Training

- 390,000 EPOS-LHC events
- 90,000 adaptive parameters
- implemented in PyTorch
- training on GPU takes 8 hours

EM dominated

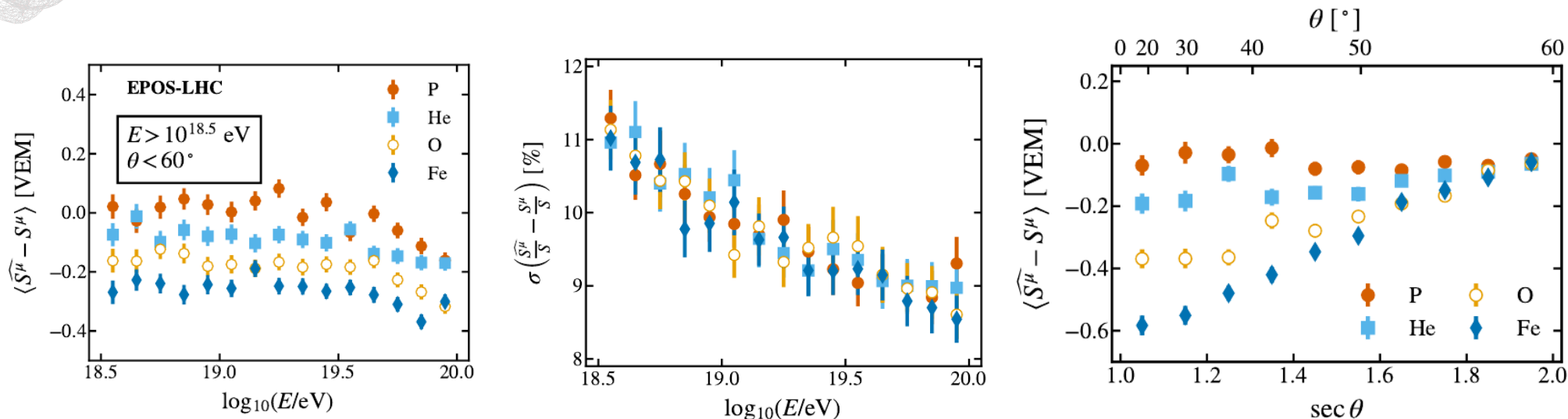


Muon dominated



- DNN successfully reconstructs muon trace
 - captures overall trend of the signal trace, but predicts a more peaky trace
 - filters out peaks which look less muonic

Evaluation on EPOS-LHC



- reconstruction improves with energy
 - ♦ composition bias evident
 - ♦ relative resolution down to 9% at the highest energies
- reconstruction performance improves with zenith
 - ♦ em-component is attenuated → traces contain larger fraction of muons signals

Application to data

DNN predicts muon traces with similar features as observed on simulation

currently no in-depth validation of method possible

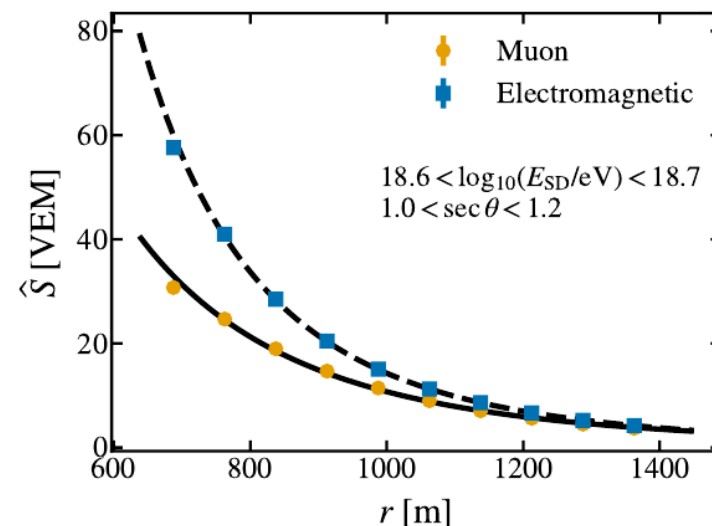
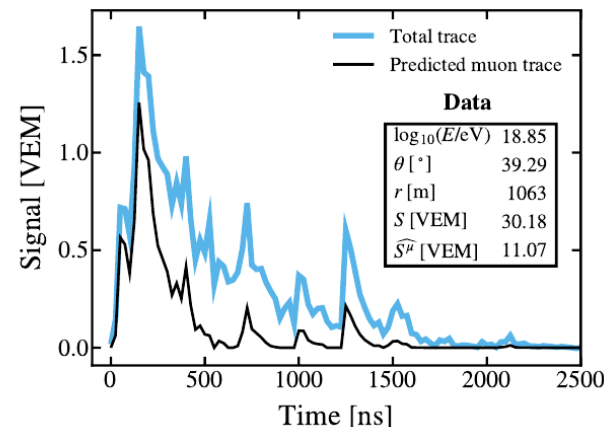
- precise measurement of muons needed

Alternative

- estimate muonic and electromagnetic part
 - crosscheck using Akeno parametrization
 - overall good match

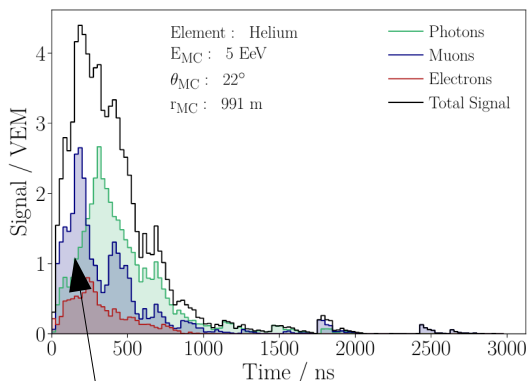
Limitations

- Hard to calibrate!
- We know: simulations have too less muons....

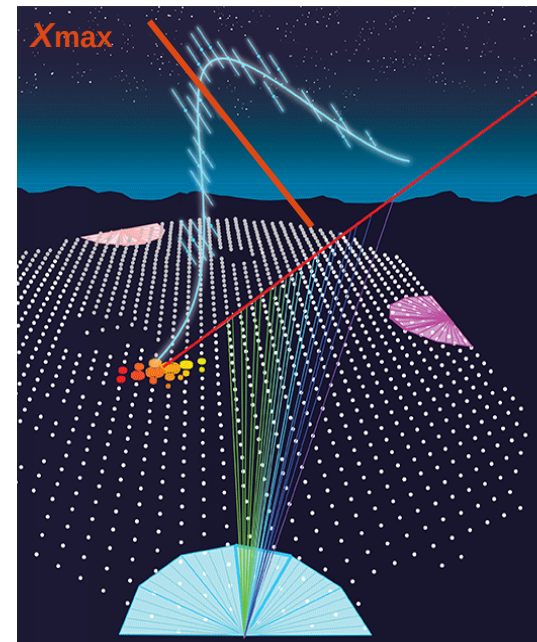
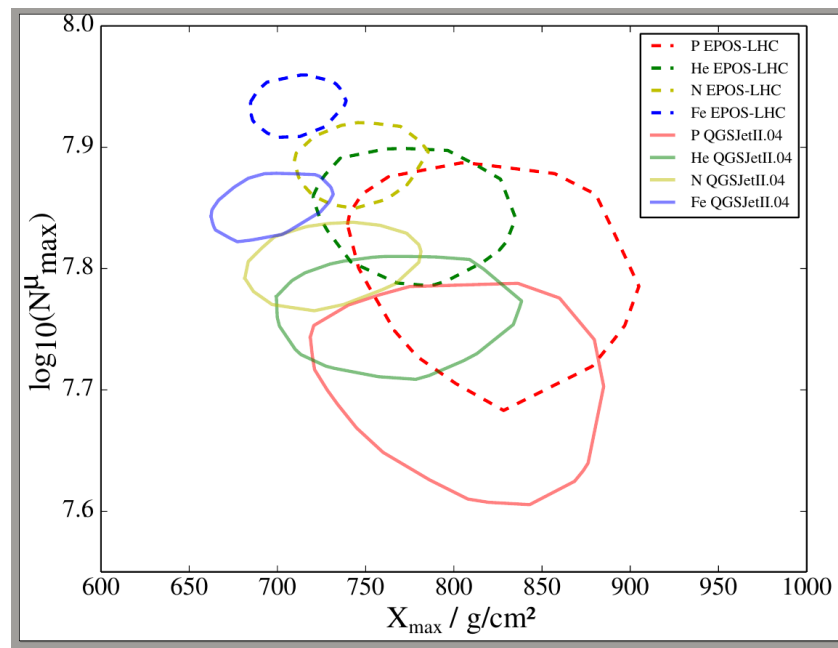


Mass composition of UHECRs

measured SD signal trace



Accessible at surface
 → Surface Detector



muons

- challenging to calibrate!
- large systematics
(muon deficit)

Longitudinal observation of the shower
 → Fluorescence Detector

X_{max}

- Simulations matching
- calibrate with FD
- control systematics

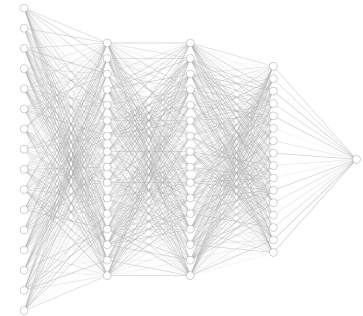
Reconstruction of $X_{\max}$

event-wise composition estimates



$X_{\max}$

shower maximum,
correlates with primary mass



How to write an ML paper



1. Identify science case

- Identify unique ML benefit

2. Design model + train

- (add physics knowledge, preprocessing!)

3. Benchmark model on simulations

- Exploit full phase space

4. Evaluate and calibrate model on data

- Validate model (Data / MC mismatch)
→ publish technical paper

5. Estimate systematics (this takes ages...)

6. Perform physics analysis (more systematics)

- publish paper & become famous

How to write an ML paper

1. Identify science case

- Identify unique ML benefit

2. Design model + train

- (add physics knowledge, preprocessing!)

3. Benchmark model on simulations

- Exploit full phase space

4. Evaluate and calibrate model on data

- Validate model (Data / MC mismatch)
→ publish technical paper

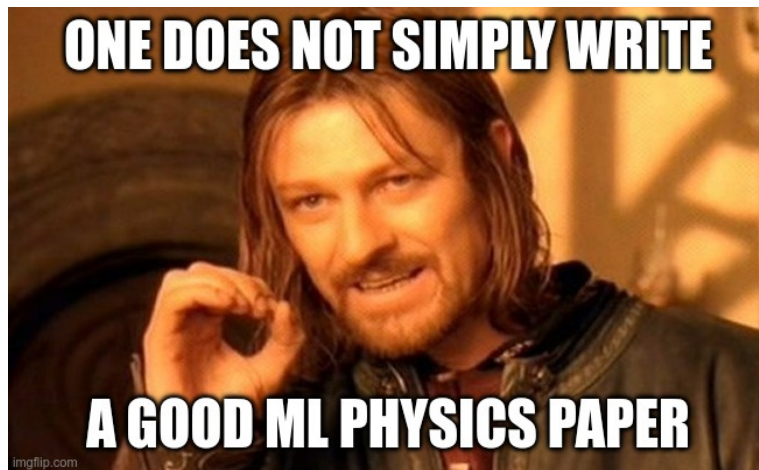
5. Estimate systematics (this takes ages...)

6. Perform physics analysis (more systematics)

- publish paper & become famous

easy

hard



How to write an ML paper



1. Identify science case

- Identify unique ML benefit

2. Design model + train

- (add physics knowledge, preprocessing!)

3. Benchmark model on simulations

- Exploit full phase space

4. Evaluate and calibrate model on data

- Validate model (Data / MC mismatch)
→ publish technical paper

5. Estimate systematics (this takes ages...)

6. Perform physics analysis (more systematics)

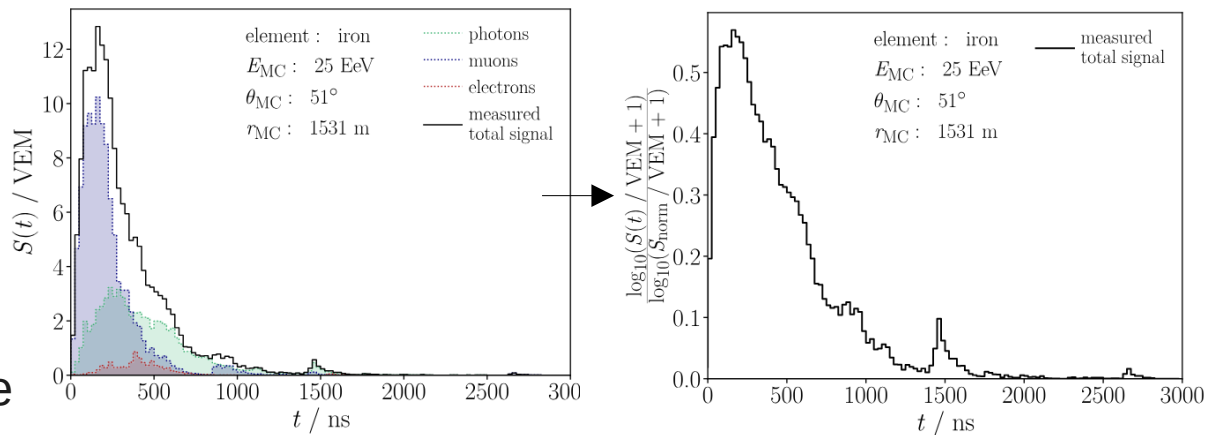
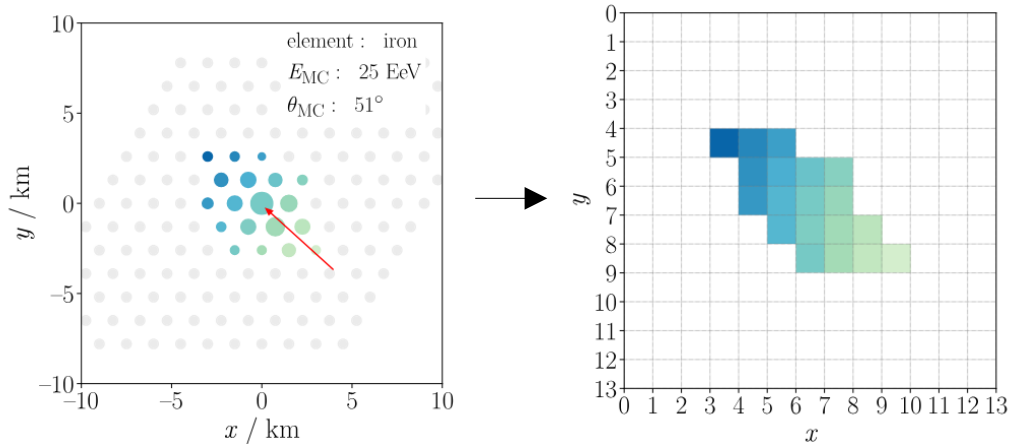
- publish paper & become famous



Data pre-processing

Pre-processing is essential → symmetries!

- DNNs are not noise robust
- DNNs are not scale-invariant
- Re-index hexagonal array
 - ♦ Into 2D Cartesian grid
 - ♦ Focus on cutout only
- Use logarithmic trace-rescaling
 - ♦ Signals follow power-law
 - ♦ Important to measured peaks
 - ♦ Cut trace to trigger window
 - relative time: additional feature

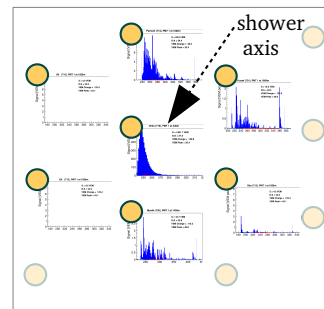


Deep-learning-based reconstruction

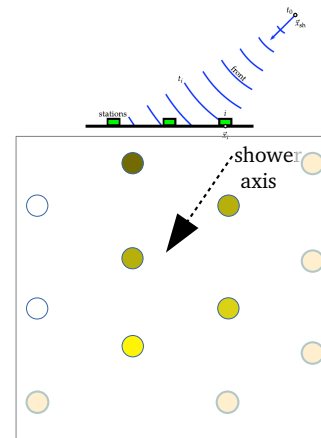
Network for reconstructing SD data

Use bidirectional LSTMs

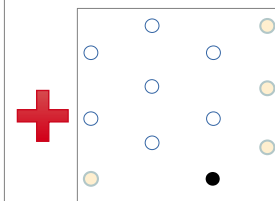
- analyze measured signals
- network shared over stations
 - same transformation applied to each station



signal traces



arrival times

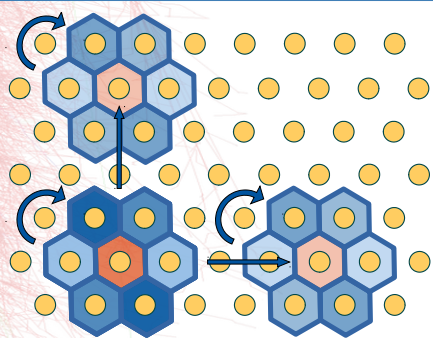


detector states

Recurrent part
analyze traces

Convolutional part
explore footprint

Xmax, E, axis, core

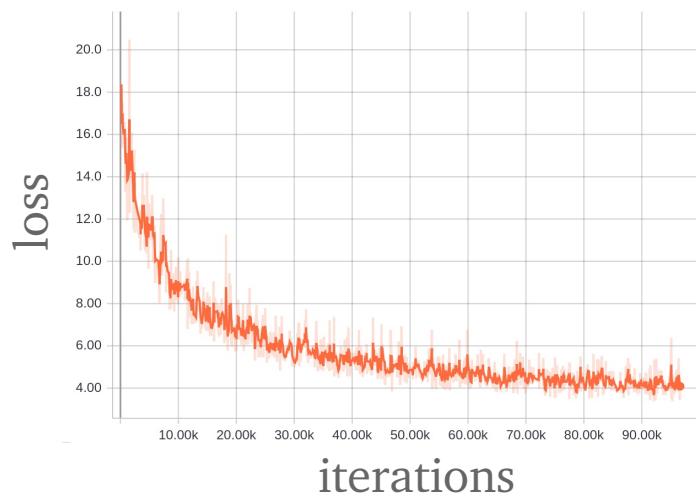


Hexagonal convolution
exploits hexagonal footprint

- hexagonal filter
- translational invariance
- rotational invariance

Neural Network: AixNet

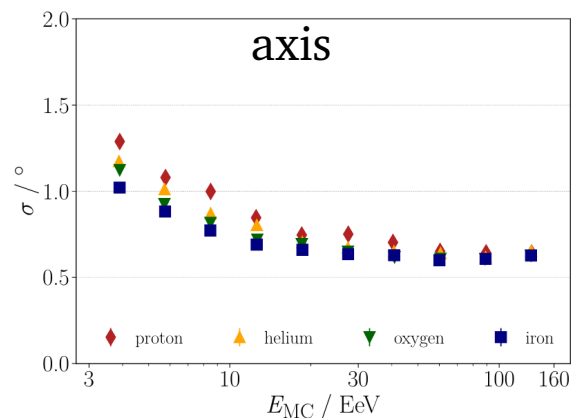
- features ~1.5 million parameters
- train with augmented simulation data
 - ♦ *mimic various detector states:
broken stations/PMTs, saturation values*
 - ♦ *training on GPU ~ 1-2 days*



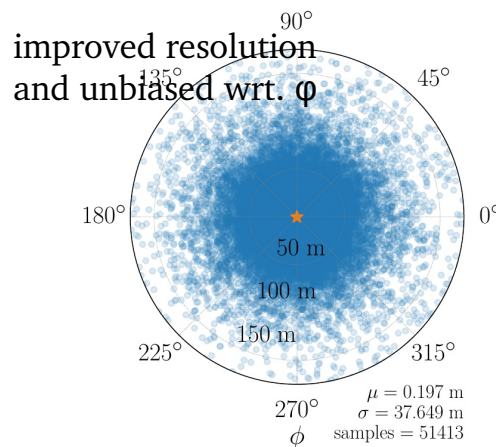
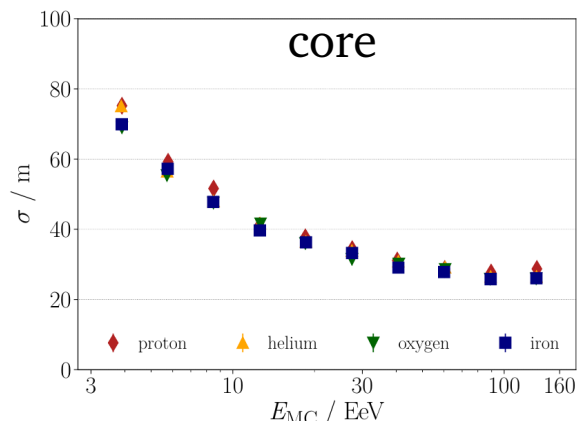
Simulated shower data	EPOS-LHC
# Showers	800,000
Training	700,000
Validation	10,000
Test	90,000
Energy	18.0 – 20.2 $\log_{10}(\text{E/eV})$
Spectrum	E^{-1}
Composition	25% proton 25% helium 25% oxygen 25% iron
Zenith	0-65°

Reconstruction of geometry and energy

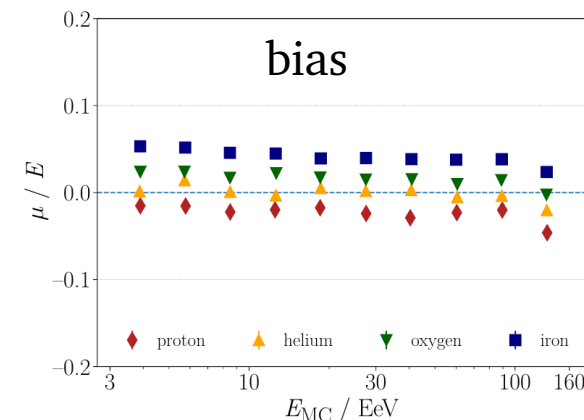
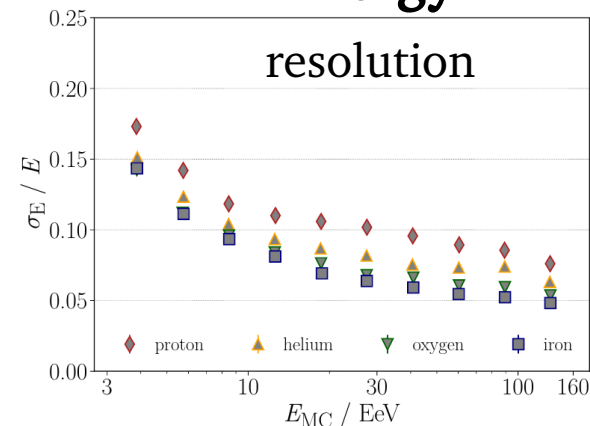
Shower geometry



- slightly worse than standard reconstruction
- deviation from optimal grid



Energy

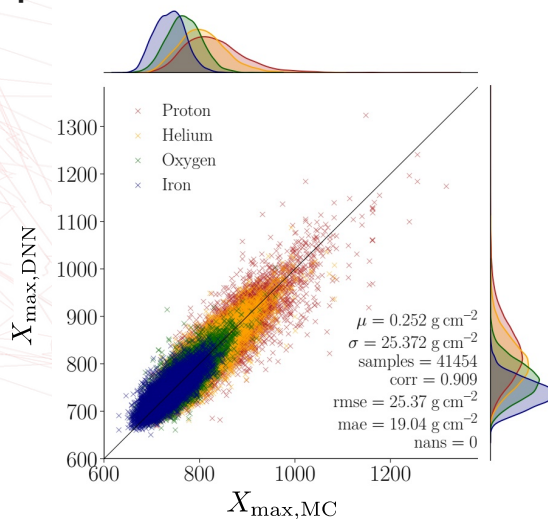


- **half** the composition bias of the standard reconstruction

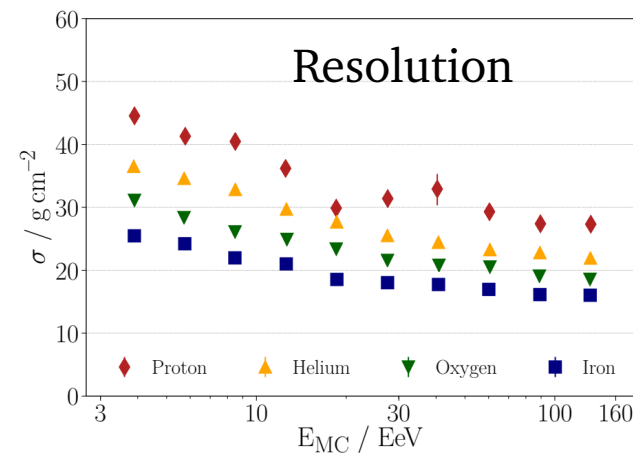
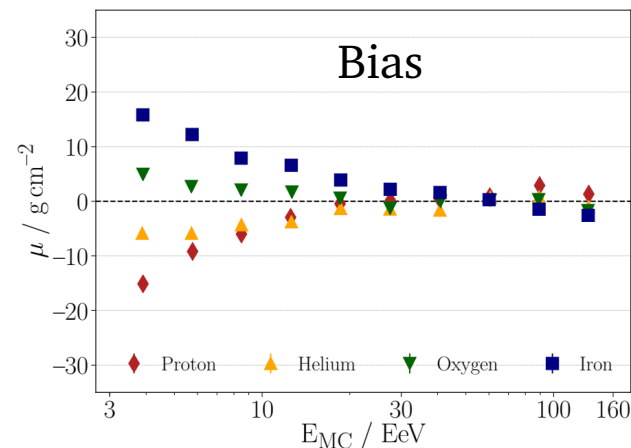
Reconstruction of $X_{\max}$

Network trained on EPOS-LHC

- investigate performance on EPOS-LHC showers



- high correlation with true $X_{\max}$
- moderate dependency on primary particle
 - performance improves with energy
- above 10 EeV: good resolution + small bias



How to write an ML paper



1. Identify science case

- Identify unique ML benefit

2. Design model + train

- (add physics knowledge, preprocessing!)

3. Benchmark model on simulations

- Exploit full phase space

4. Evaluate and calibrate model on data

- Validate model (Data / MC mismatch)
→ publish technical paper

5. Estimate systematics (this takes ages...)

6. Perform physics analysis (more systematics)

- publish paper & become famous



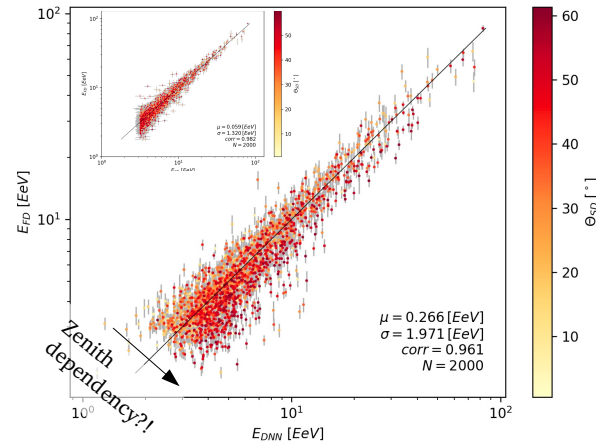
A. Aab (Pierre Auger Collaboration) et al., JINST 16 P07019 (2021)

A. Abdul Halim (Pierre Auger Collaboration) et al., Phys. Rev. Lett. 134, 021001 (2025)

A. Abdul Halim (Pierre Auger Collaboration) et al., Phys. Rev. D 111, 022003 (2025)

Application to Auger data

crosschecks, crosschecks, crosschecks



Study full phase space!

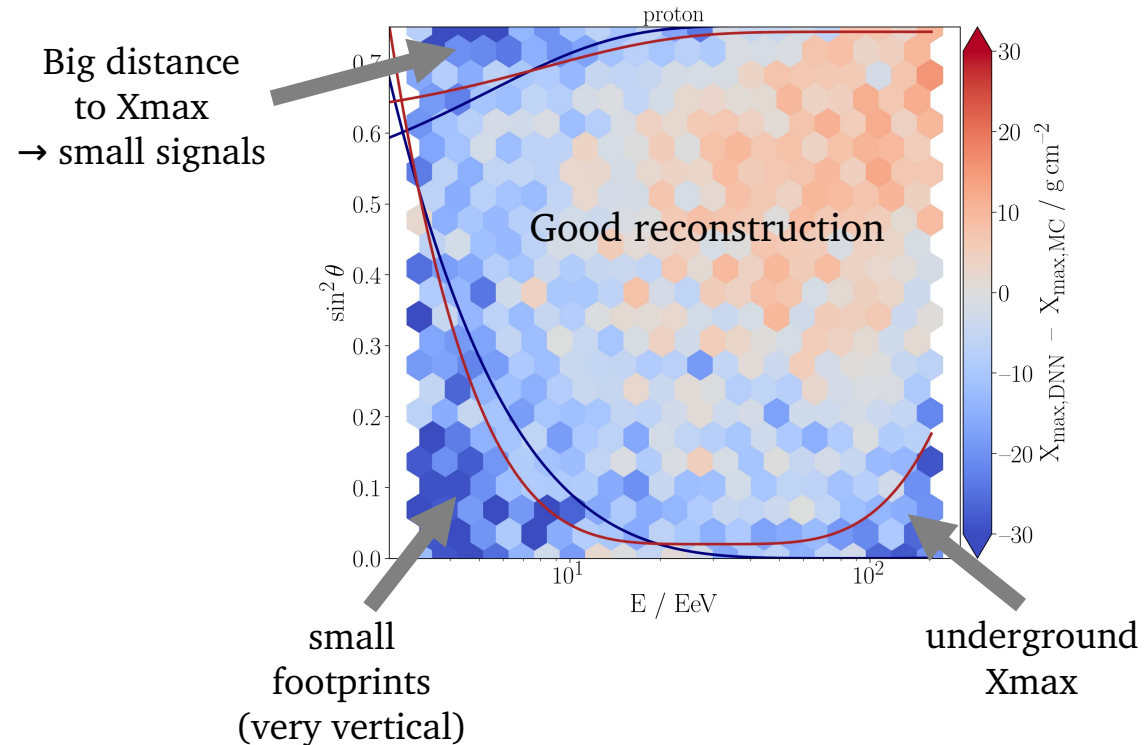
Investigate performance → full phase space

Detailed analysis → check for biases!

- Azimuth
- Zenith
- Core distance
- Saturation
- Composition
- Energy
- Xmax

fiducial SD selection

- bias is energy-zenith dependent
- select high-quality phase space

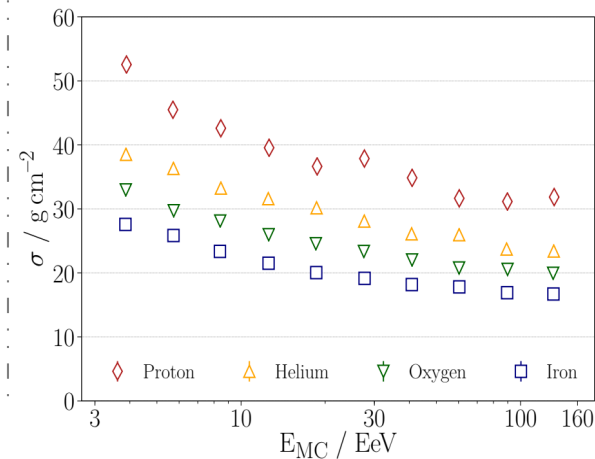
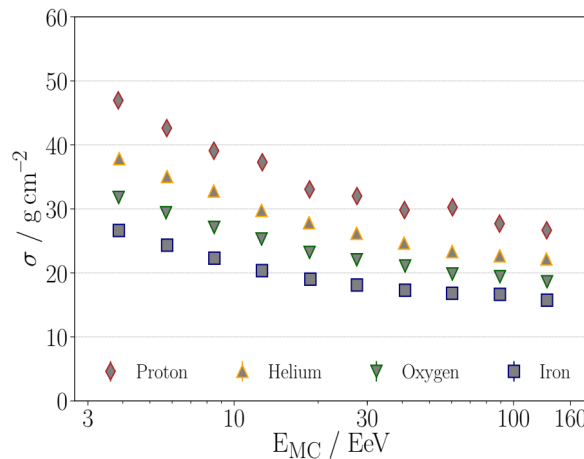
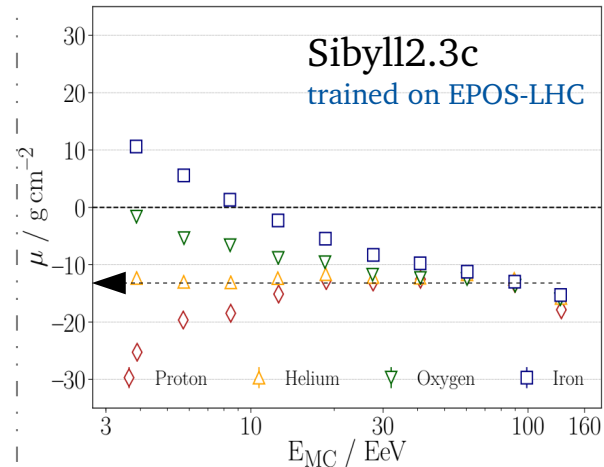
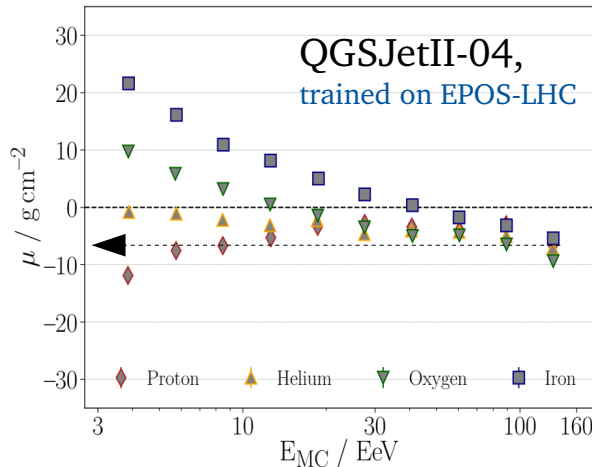


Evaluation – Additional Interaction Models

DNN trained using EPOS LHC

Evaluation using:

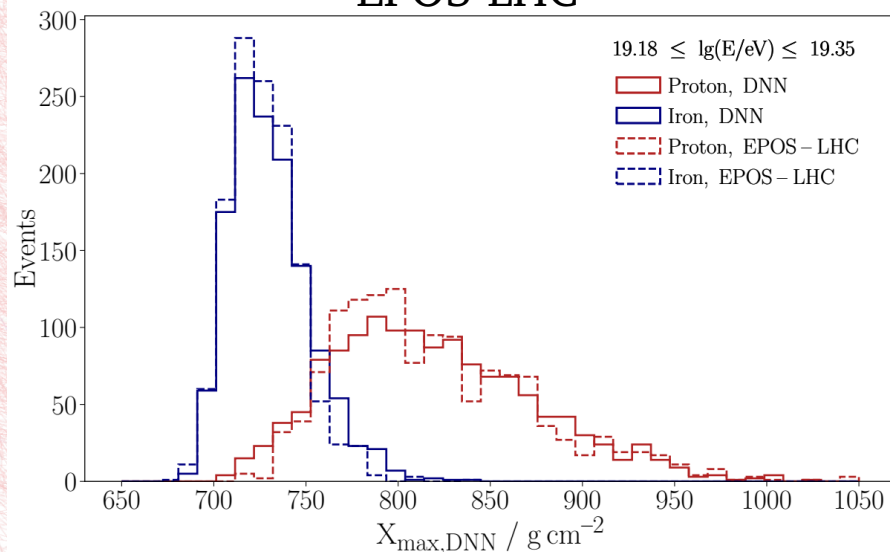
- QGSJET-II.04
- SIBYLL2.3c
- similar resolution
 - ♦ interaction model independent
- bias different
 - ♦ negative for both models
 - ♦ depends on interaction model



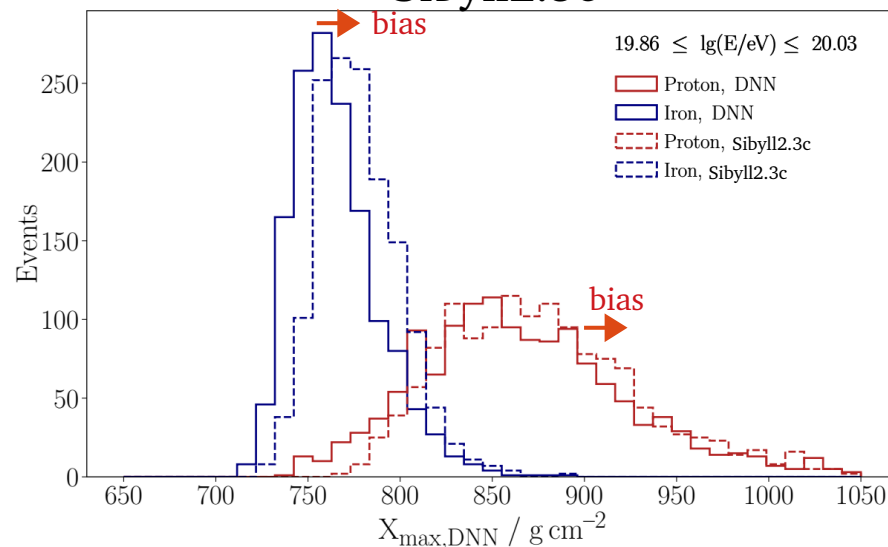
Reconstructed Xmax distributions

- check reconstructed Xmax distributions for various hadronic models
- absolute bias clearly visible, as expected (Sibyll2.3 = -15 g/cm²)
- overall shape reconstructed correctly
- calibration to Xmax-scale of the FD needed for measuring Xmax distributions

EPOS-LHC



Sibyll2.3c



How to write an ML paper

1. Identify science case

- Identify unique ML benefit

2. Design model + train

- (add physics knowledge, preprocessing!)

3. Benchmark model on simulations

- Exploit full phase space

4. Evaluate and calibrate model on data

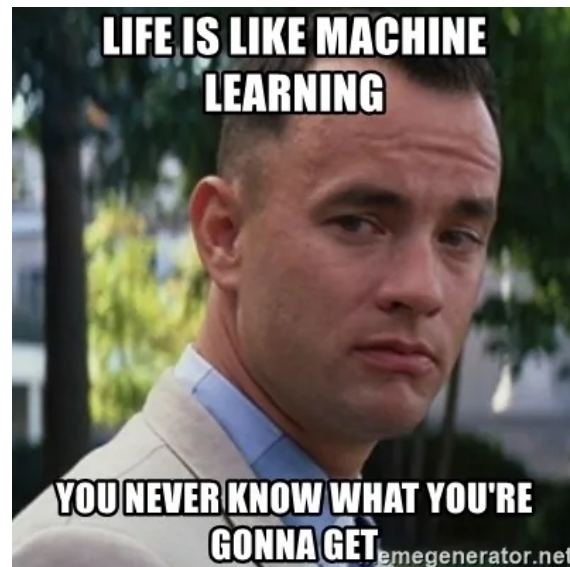
- Validate model (Data / MC mismatch)

→ publish technical paper → [A. Aab \(Pierre Auger Collaboration\) et al., JINST 16 P07019 \(2021\)](#)

5. Estimate systematics (this takes ages...)

6. Perform physics analysis (more systematics)

- publish paper & become famous



A. Aab (Pierre Auger Collaboration) et al., JINST 16 P07019 (2021)

A. Abdul Halim (Pierre Auger Collaboration) et al., Phys. Rev. Lett. 134, 021001 (2025)

A. Abdul Halim (Pierre Auger Collaboration) et al., Phys. Rev. D 111, 022003 (2025)

Application to Auger data

crosschecks, crosschecks, crosschecks

Hybrid data

FD + SD reconstruction

fiducial FD selection

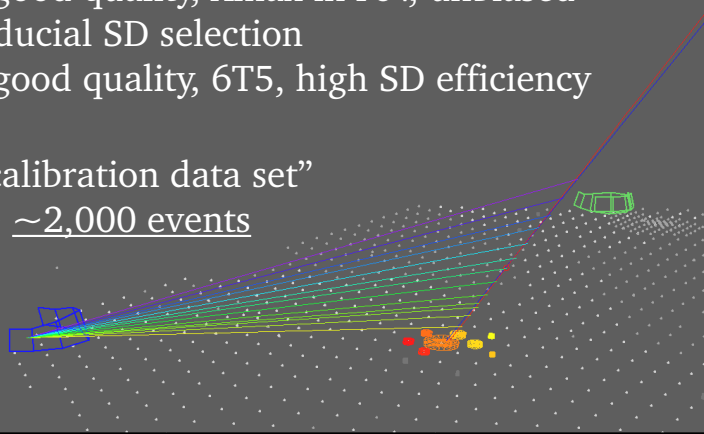
good quality, X_{max} in FoV, unbiased

fiducial SD selection

good quality, 6T5, high SD efficiency

“calibration data set”

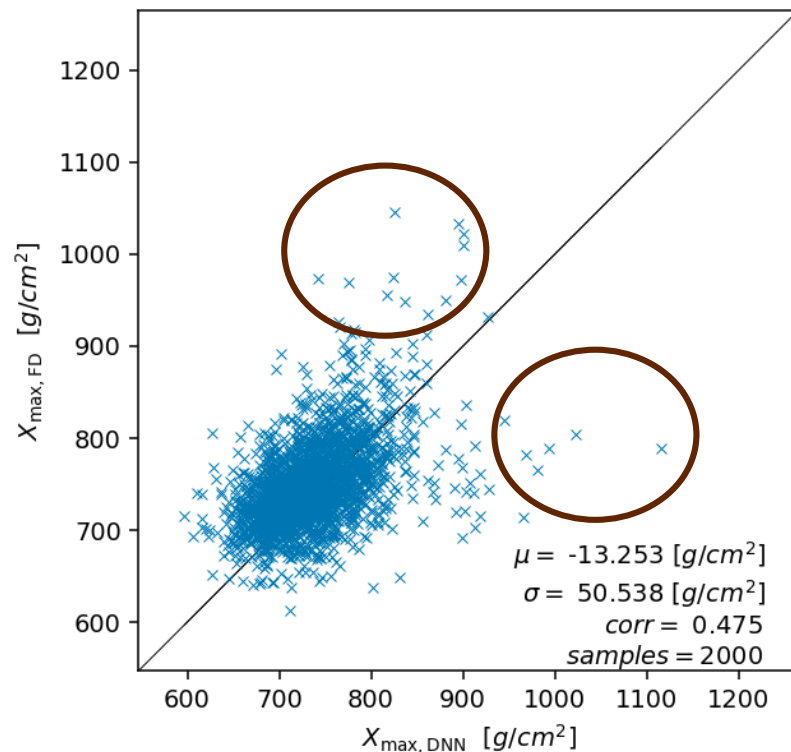
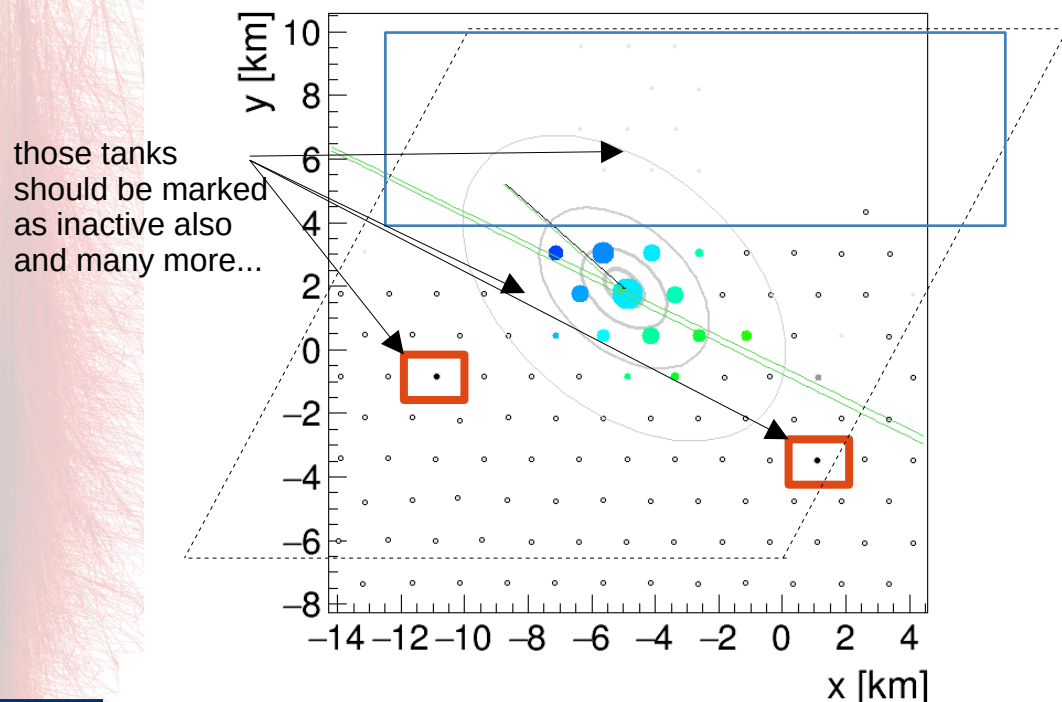
→ ~2,000 events



MC-data mismatch: first applications to hybrid data

DNN showed strange outliers

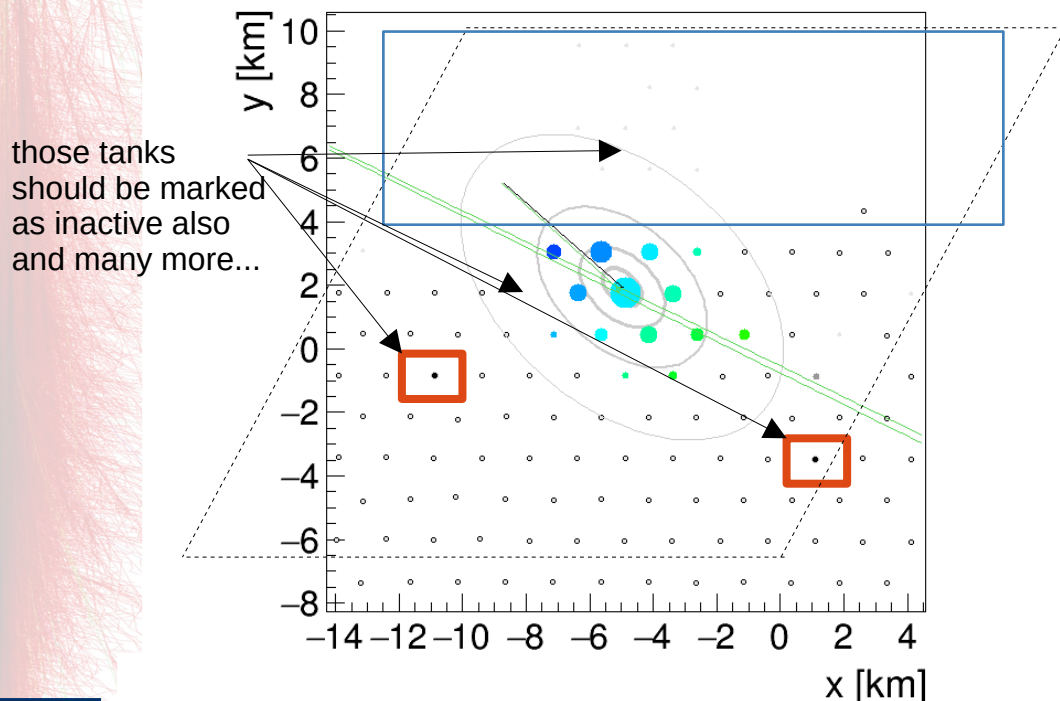
- Data-simulation mismatch! → broken stations in data but not in simulations
→ train with inactive tanks! (masking)



MC-data mismatch: first applications to hybrid data

DNN showed strange outliers

- Data-simulation mismatch! → broken stations in data but not in simulations
→ train with inactive tanks! (masking)



Status maps

additionally provided during training and evaluation

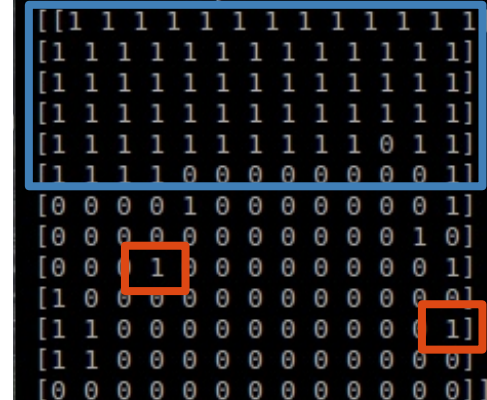
→ During training drop stations

→ Poisson distribution

→ still enforce trigger conditions

→ retrain model!

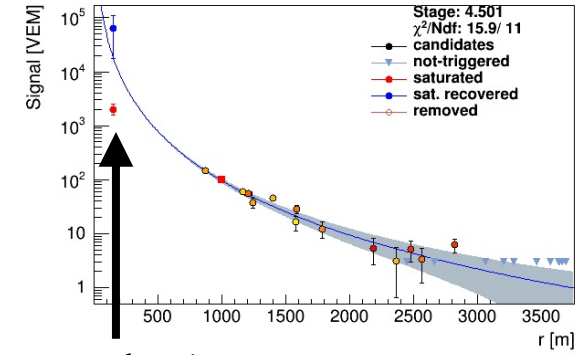
blacktank map:



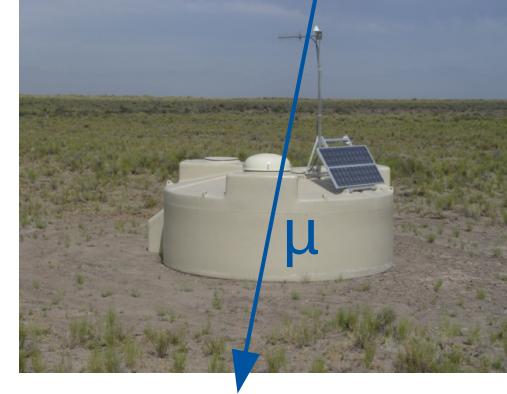
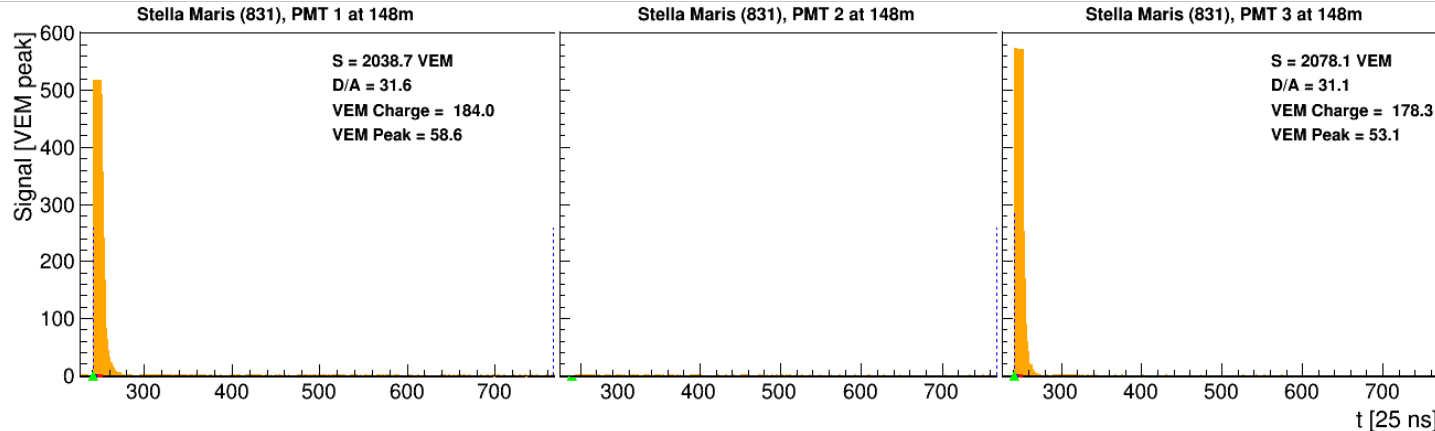
1 = broken
0 = working

Broken PMTs & calibration of VEM traces

- Every PMT has slightly different working point
 - VEM trace is calibrated using muons
 - 1 VEM $\rightarrow$ some ADC channels (estimate in calibration)
 - $\rightarrow$ each PMT has different saturation point (but same saturation in simulations)
- Implement variable saturation during training



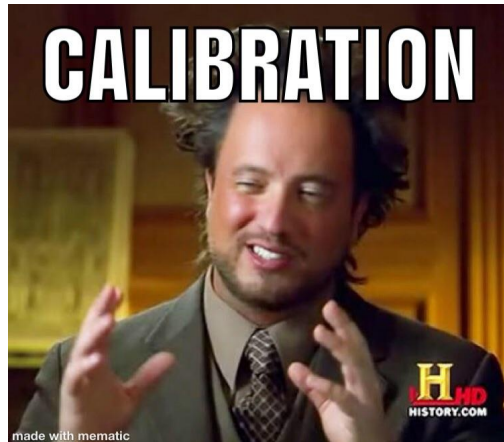
Saturated station



Application to Auger data

calibrations, calibrations, calibrations

and crosscheck, crosschecks, crosschecks ...



A. Aab (Pierre Auger Collaboration) et al., JINST 16 P07019 (2021)

A. Abdul Halim (Pierre Auger Collaboration) et al., Phys. Rev. Lett. 134, 021001 (2025)

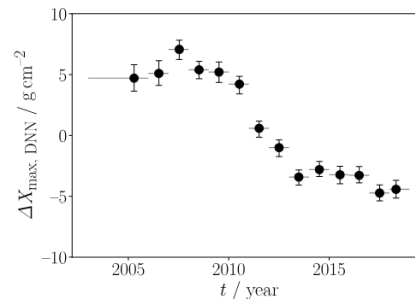
A. Abdul Halim (Pierre Auger Collaboration) et al., Phys. Rev. D 111, 022003 (2025)

SD-Based Calibrations of the DNN

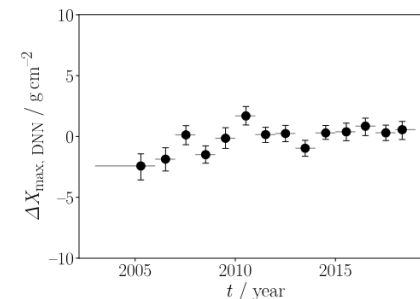
Calibrate DNN using SD-1500 data

→ study with respect to average prediction

- correction for detector ageing effects
 - ♦ calibrate using monitoring observable
- time-dependent corrections
 - ♦ seasonal variations $\sim 2 \text{ g/cm}^2$
 - ♦ diurnal variations $\sim 1 \text{ g/cm}^2$
- angular-dependent calibration
 - ♦ variations with azimuth $\sim 2.5 \text{ g/cm}^2$

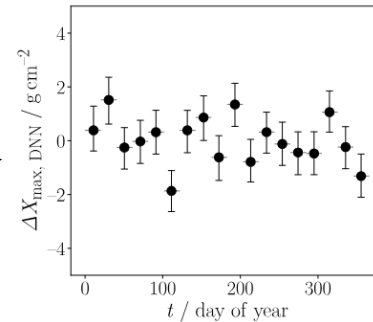
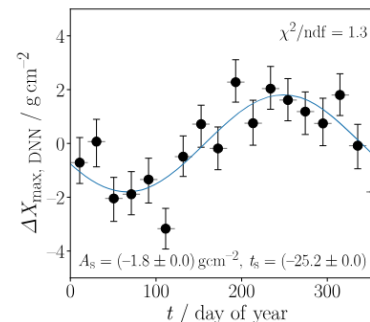


before calibration

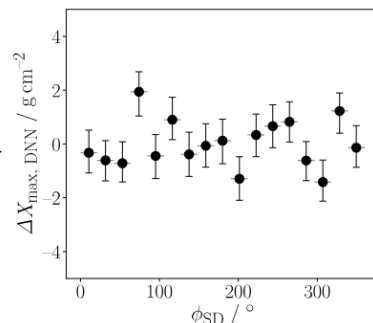
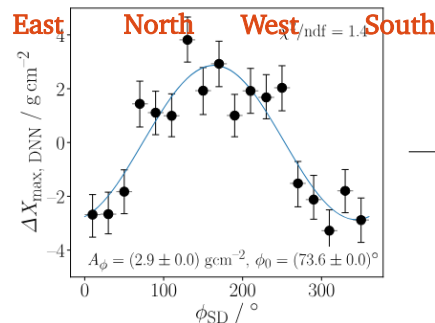


after calibration

seasonal



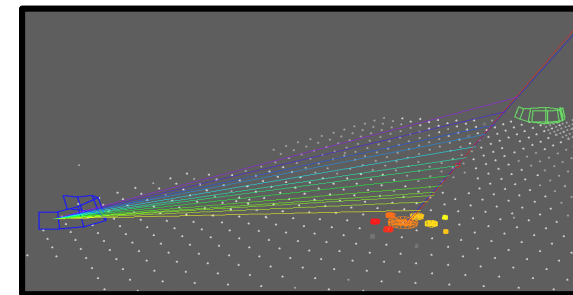
azimuth



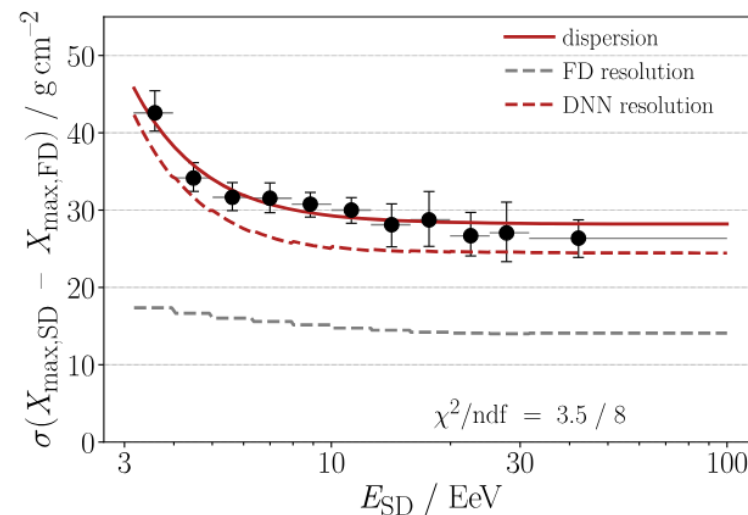
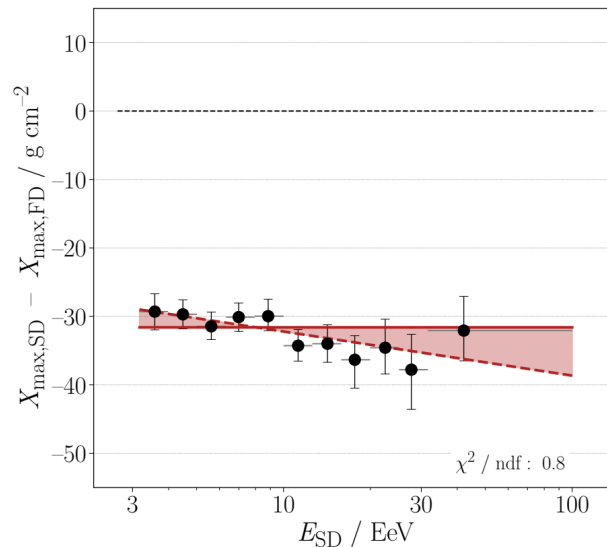
Application to measured hybrid data

Use hybrid events to perform calibration to the FD $X_{\max}$ scale

- **correlation 0.67** (>0.6 when corrected for elongation rate)
- **resolution matches** expectations
- **-30 g/cm² bias** (hadronic int. models, detector simulation)
 - ♦ independent of energy $\rightarrow$ calibration



After FD calibration
interaction-model
dependence removed!



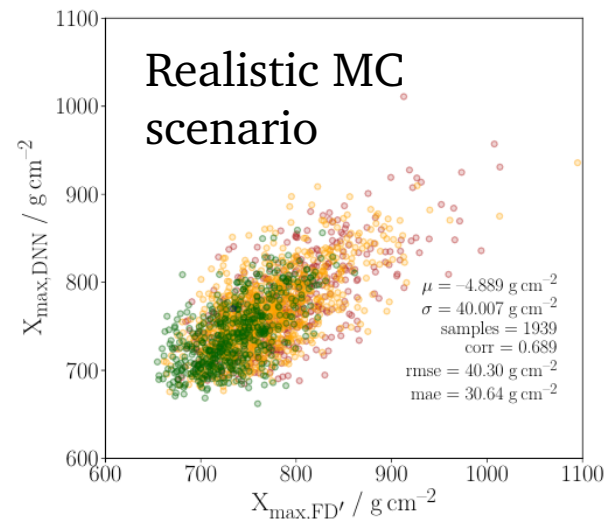
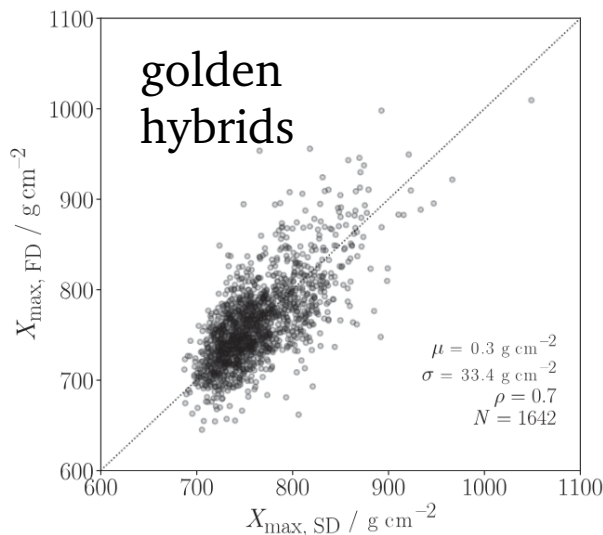
Absolute calibration using the FD

Use hybrid events to perform calibration to the FD $X_{\max}$ scale

- **correlation 0.67** (>0.6 when corrected for elongation rate)
- **resolution matches** expectations
- **-30 g/cm^2 bias** (hadronic models, detector simulation)
 - ♦ independent of energy $\rightarrow$ calibration

Correlation & resolution
matches expectations,
assuming

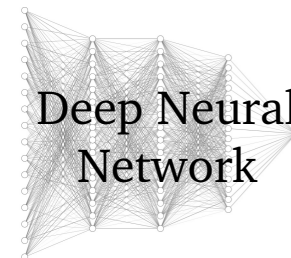
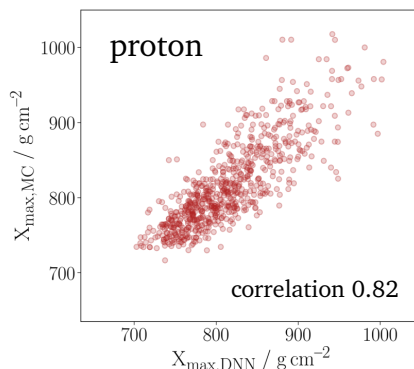
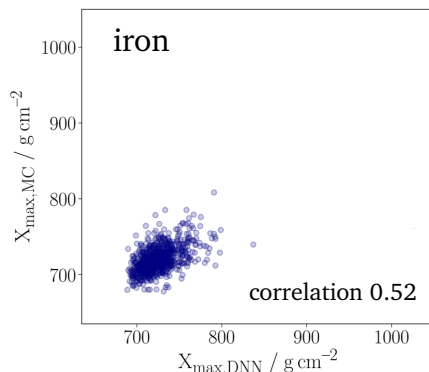
- $\rightarrow$ FD composition
- $\rightarrow$ Auger energy spectrum



Comparison DNN vs traditional method

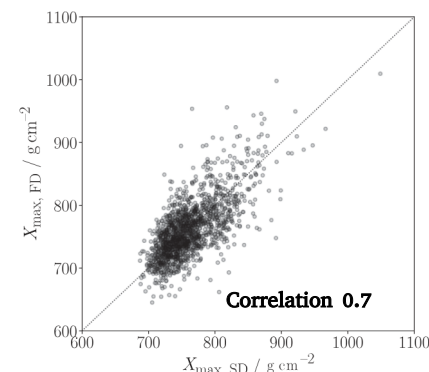
A.Aab et al. (Pierre Auger Collaboration), JINST 16 P07019 (2021)

Simulations

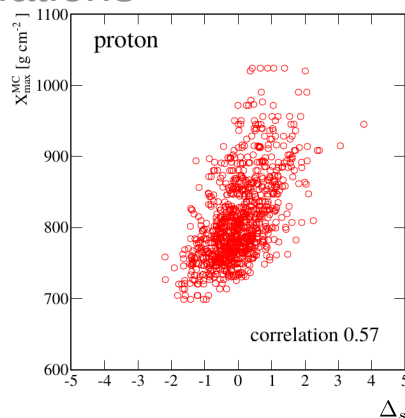
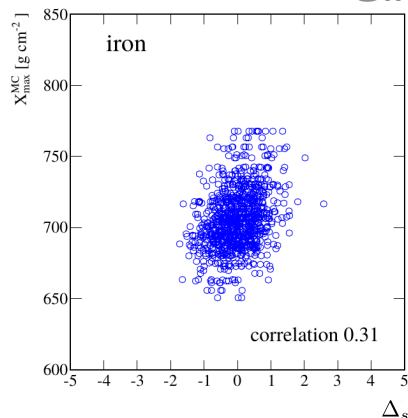


**improvement of DNN
by almost 50% (correlation)**

Hybrid Data

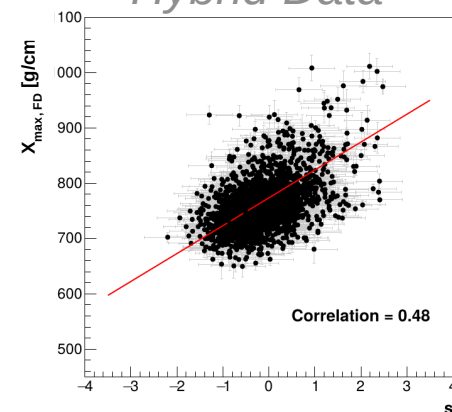


Simulations



Delta Method
determines composition
via rise time of signal

Hybrid Data



How to write an ML paper



1. Identify science case

- Identify unique ML benefit

2. Design model + train

- (add physics knowledge, preprocessing!)

3. Benchmark model on simulations

- Exploit full phase space

4. Evaluate and calibrate model on data

- Validate model (Data / MC mismatch)

→ publish technical paper → A. Aab (Pierre Auger Collaboration) et al., JINST 16 P07019 (2021)

5. Estimate systematics (this takes ages...)



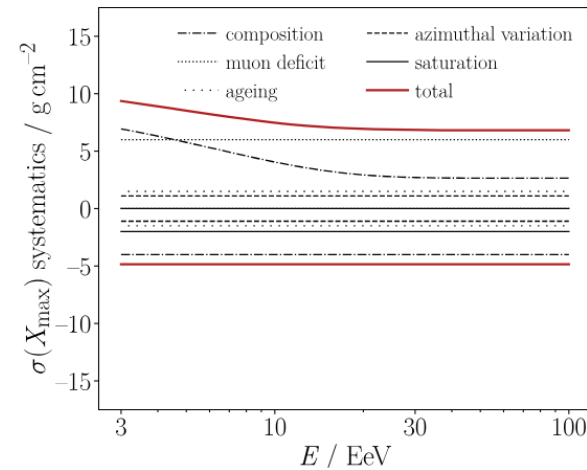
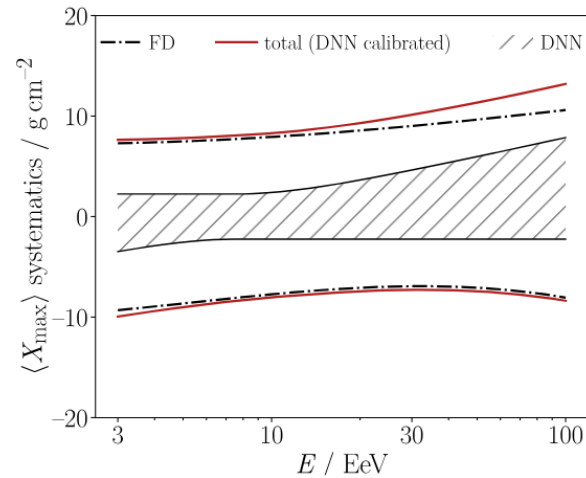
6. Perform physics analysis (more systematics)

- publish paper & become famous

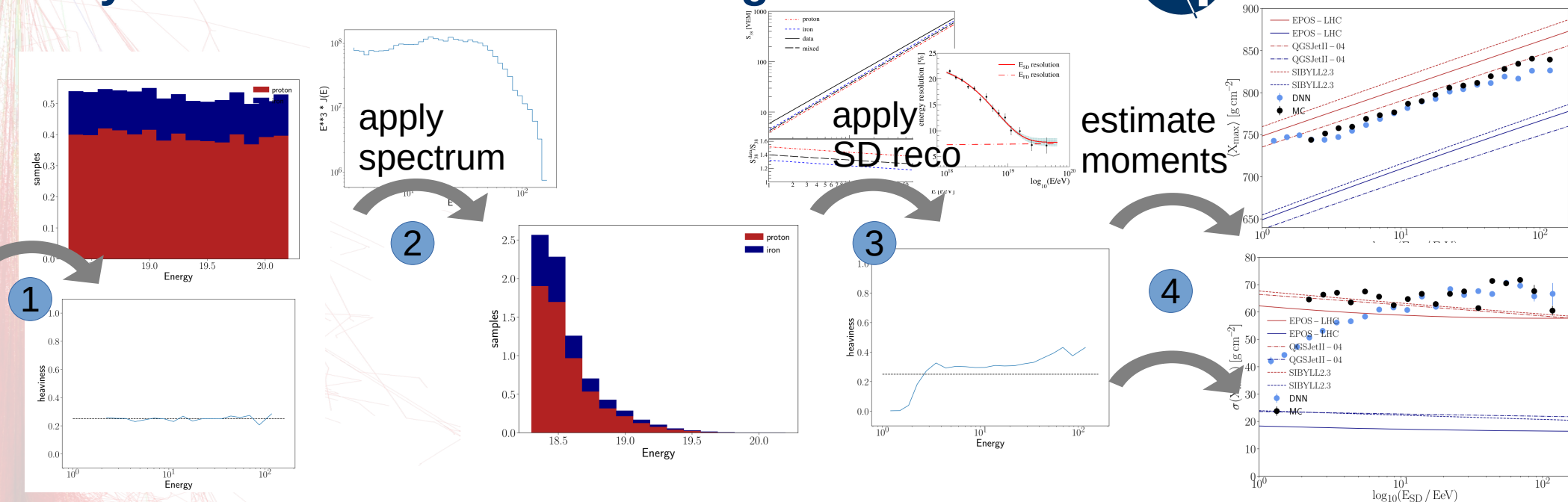
Application to Auger data

Systematics

Derived from crosschecks and calibrations



Systematics → forward folding



1. Data / MC

Choose
composition e.g.
 $p / Fe = 3:1$
AugerMix (realistic)

2. Data / MC

Apply Auger spectrum
Same for each element

Resample (x 20,000)

3. only Data

Apply SD
• **reconstruction**
• **calibration**

4. Data / MC

- Fid. SD Cut
- Calc. 1st & 2nd moment for Data and MC

Performance on simulations

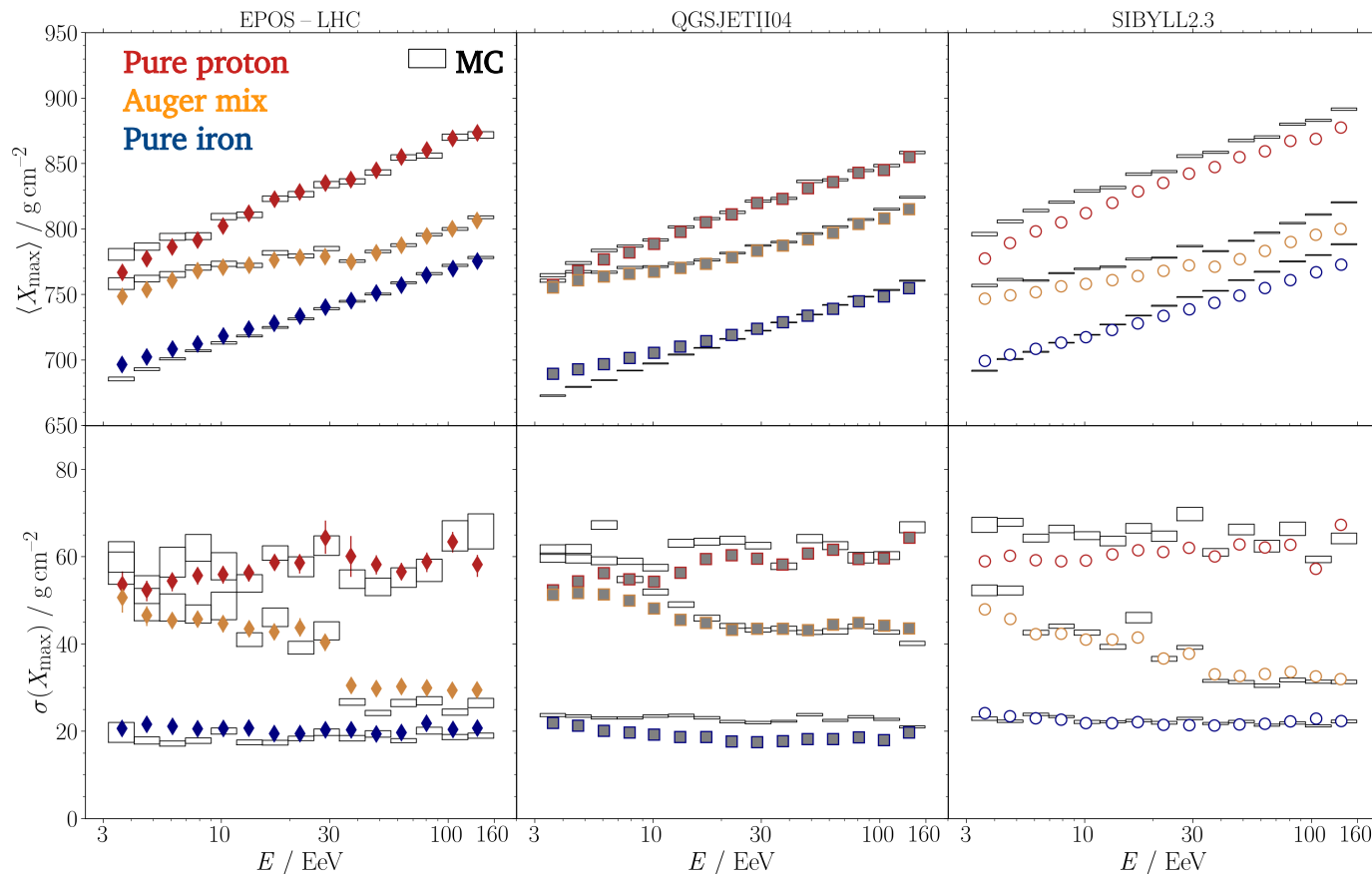
Compare reconstructed to injected compositions

Interaction model bias:

- 1st moment:
 - QGSJet: -5 g/cm²
 - ♦ Sibyll2.3: -12 g/cm²
- 2nd moment:
- no strong dependency

Composition bias:

- small for auger mix
- for proton and iron small beyond 10 EeV



How to write an ML paper

1. Identify science case

- Identify unique ML benefit

2. Design model + train

- (add physics knowledge, preprocessing!)

3. Benchmark model on simulations

- Exploit full phase space

4. Evaluate and calibrate model on data

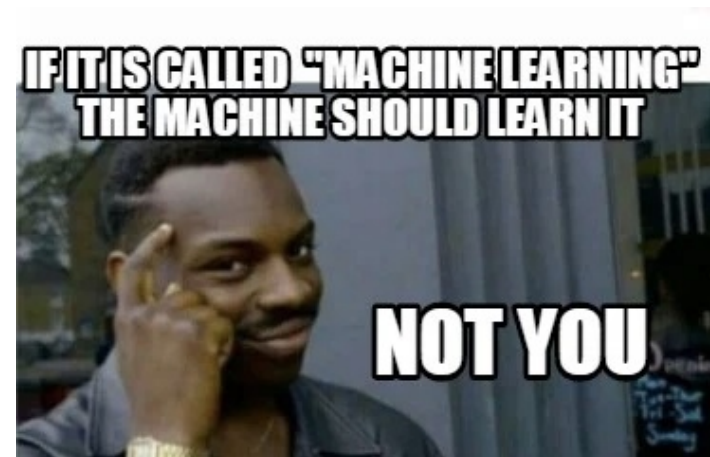
- Validate model (Data / MC mismatch)

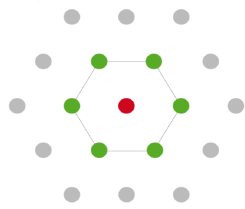
→ publish technical paper → A. Aab (Pierre Auger Collaboration) et al., JINST 16 P07019 (2021)

5. Estimate systematics (this takes ages...)

6. Perform physics analysis (more systematics)

- publish paper & become famous





Application to Auger data

crosschecks, crosschecks, crosschecks

Hybrid data

FD + SD reconstruction
fiducial FD selection
good quality, Xmax in FoV, unbiased
fiducial SD selection
good quality, 6T5, high SD efficiency

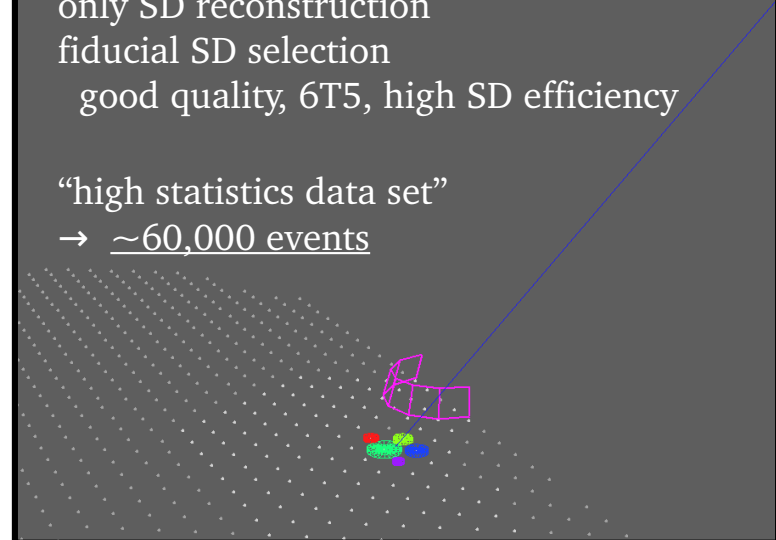
“calibration data set”
→ ~2,000 events



SD1500 data

only SD reconstruction
fiducial SD selection
good quality, 6T5, high SD efficiency

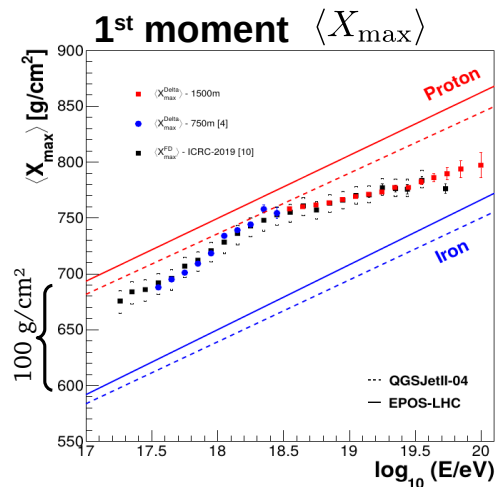
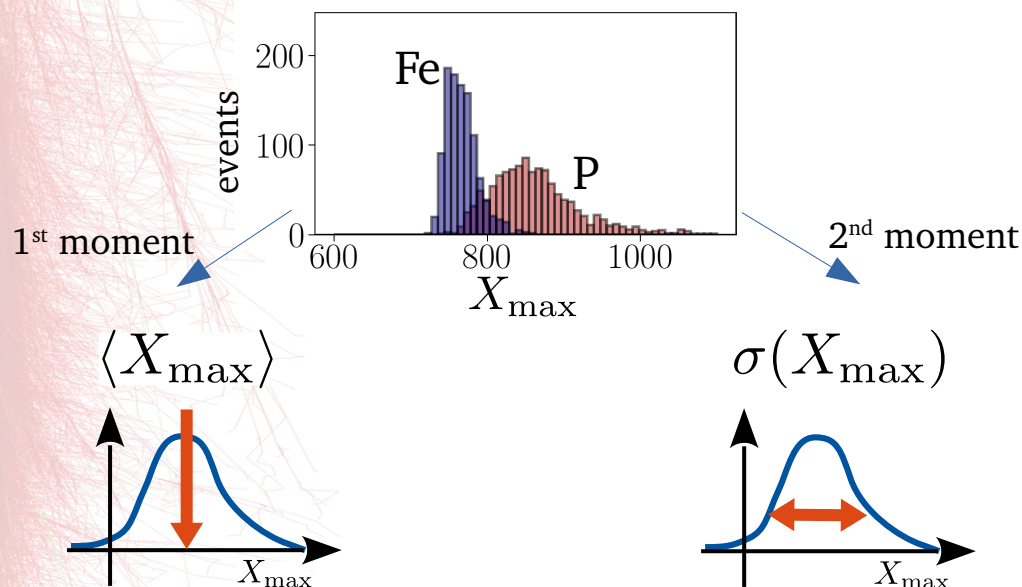
“high statistics data set”
→ ~60,000 events



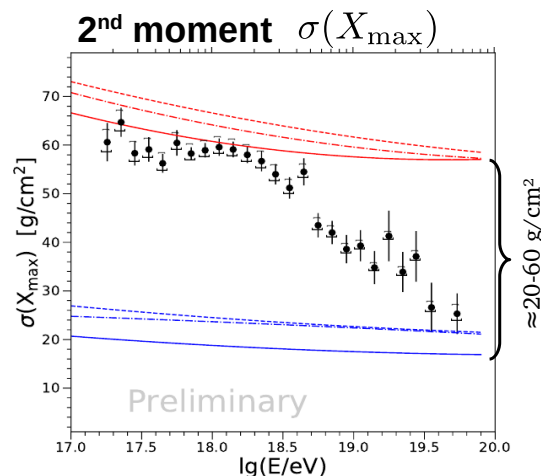
Mass composition of UHECRs

Mass composition of UHECRs

- currently: most precise mass estimator by reconstructing shower maximum $X_{\max}$
- determine composition by studying the measured $X_{\max}$ distributions



Measurement of
“average
composition”
→ low stat. err.
→ high sys. Err.



Measurement of
“composition mix”
→ high stat. err.
→ low sys. Err.

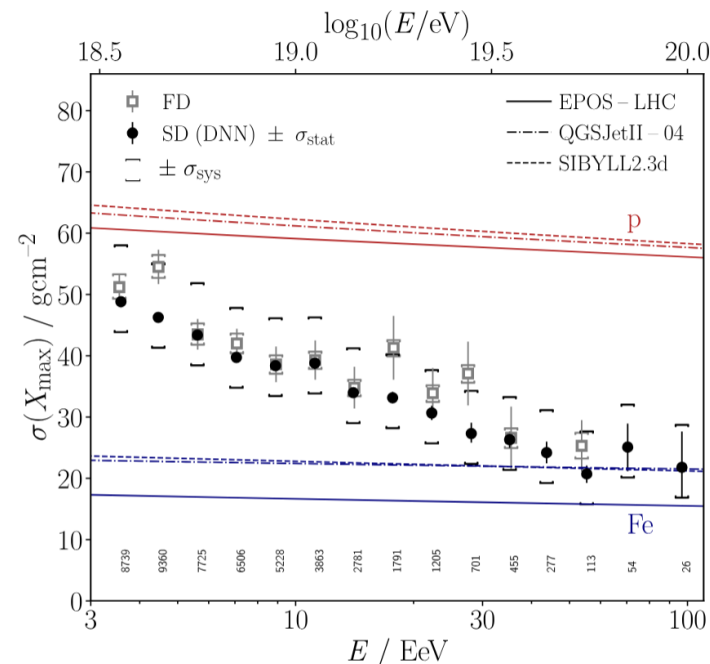
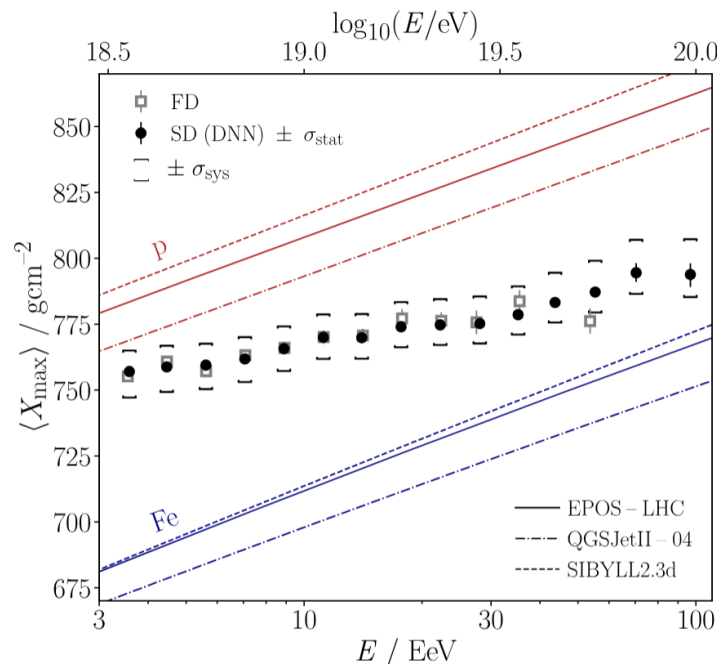
Application to SD-1500 data

SD-1500 data

High-quality selection

48,824 events

10-fold increase in
statistics compared to FD
Data taking: 2004 - 2019



- Transition from lighter to heavier and purer composition
 - excellent agreement with FD of same data-taking period (ICRC'19)
- At highest energies small fluctuations → pure and heavy composition
 - large fraction of protons and light primaries incompatible with measurement at high energies

Evidence for breaks in the elongation rate

Critical for understanding astrophysical sources

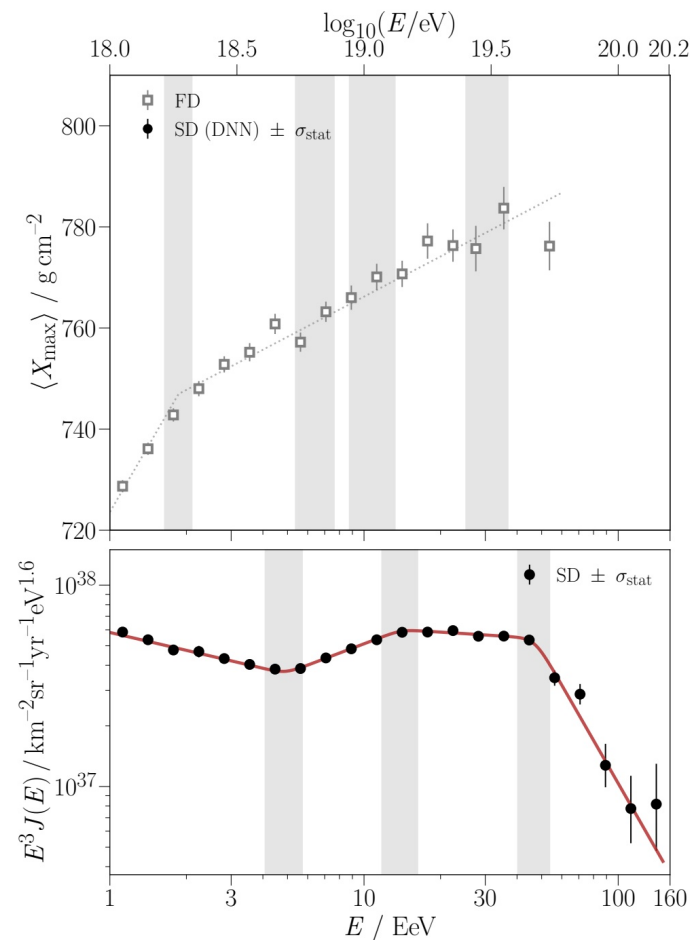
- Energy spectrum feature (deviations from simple power law)
- Evolution of mass composition

Telescope-based measurements:

- Linear model describes transition from light to heavy

Current interpretation:

- Ankle: transition from galactic to extra galactic
- Cut-off: maximum injection energy accelerator & propagation?



Evidence for breaks in the elongation rate

Critical for understanding astrophysical sources

- Energy spectrum feature (deviations from simple power law)
- Evolution of mass composition

Telescope-based measurements:

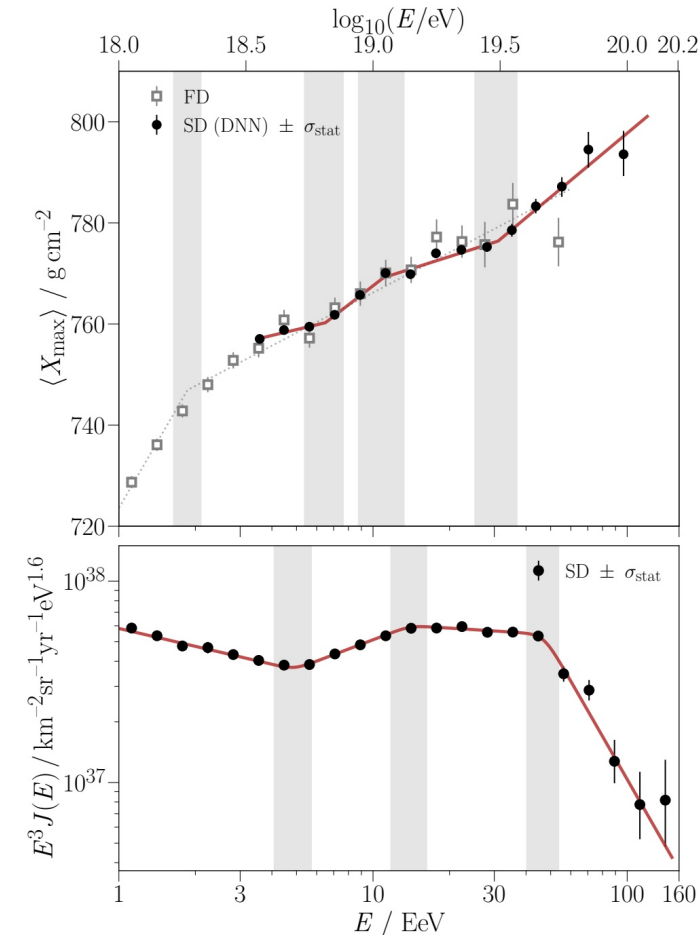
- Linear model describes transition from light to heavy

Surface-detector based (utilizing **deep learning**): statistics x10

- Evidence for three breaks, in proximity of spectrum features
same statistic: telescopes would need to operate for 150 years!

Current interpretation:

- Ankle: transition from galactic to extra galactic
- Cut-off: maximum injection energy accelerator & propagation?



How to write an ML paper

1. Identify science case

- Identify unique ML benefit

2. Design model + train

- (add physics knowledge, preprocessing!)

3. Benchmark model on simulations

- Exploit full phase space

4. Evaluate and calibrate model on data

- Validate model (Data / MC mismatch)

→ publish technical paper →

5. Estimate systematics (this takes ages...)

6. Perform physics analysis (more systematics)

- publish paper & become famous

2017

2018-2021

2019

2019-2021

JINST 16 P07019 (2021)

2021-2024

2025

Phys. Rev. D 111, 022003

Phys. Rev. Lett. 134, 021001

around 7 years

Take home messages

1. Symmetry is key (omit only if you have a hell of compute)

- Adding physics priors boosts performance

2. You need good compute

- You need GPUs, getting a final model takes time...

3. Use proper metrics

- Standard metrics might be odd for your science case

4. Don't over-optimize your model

- Challenge: robustness, don't fight for 10% MC performance

5. Calibration is key (“well, *your DNN is a black box...*”)

- Validate and calibrate (if possible with 2nd detector)

6. Become an expert on systematics

- DNN systematics are often different → crosschecks!

7. Relax: All good things take time and ML will come

2017

2018-2021

2019

2019-2021

JINST 16 P07019 (2021)

2021-2024

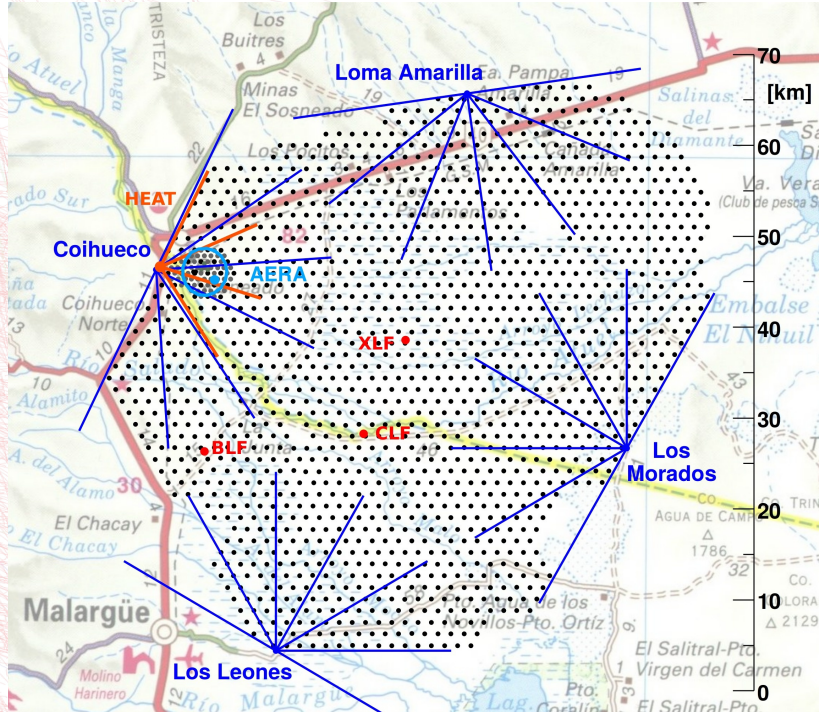
2025

Phys. Rev. D 111, 022003

Phys. Rev. Lett. 134, 021001

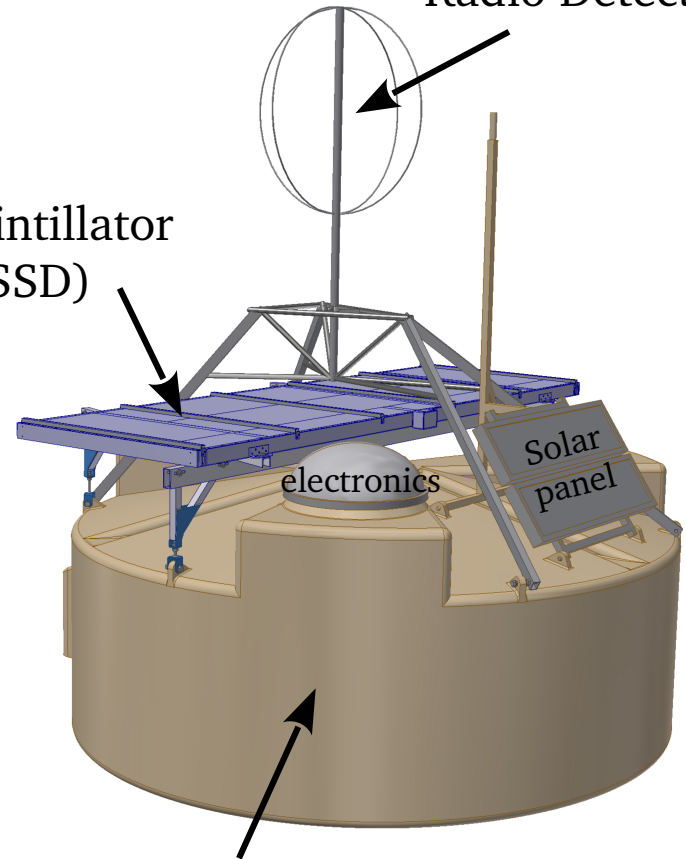
around 7 years ↓

AugerPrime Upgrade

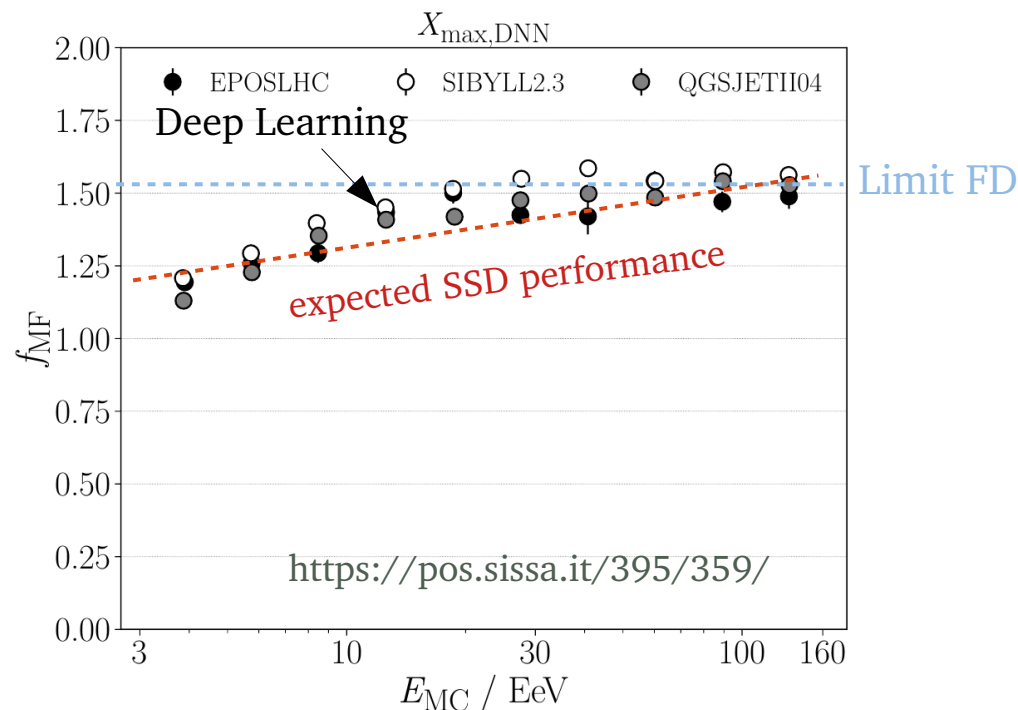


Surface Scintillator
Detector (SSD)

Radio Detector



Water-Cherenkov Detector (WCD)



Merit factor

$$f_{MF} = \frac{|\langle S_i \rangle - \langle S_j \rangle|}{\sqrt{\sigma(S_i)^2 + \sigma(S_j)^2}}$$

Mass composition studies

- Deep learning is a milestone!
 - ♦ deep learning for WCDs only
 - Similar to AugerPrime expectations
- current limit: X_{max} & simulations

Neutrino & photon searches

- identification of EM / muon signals

ML close to the sensors

- use ML for triggering of showers
- increase sensitivity to faint showers

Summary



ERLANGEN CENTRE
FOR ASTROPARTICLE
PHYSICS



Deep learning is game changer → analyze signal traces (exploit correlations in n-D data)

Deep Learning at the Pierre Auger Observatory:

- extract mass-sensitive information, improved event reconstruction
- refinement of simulations, arrival direction searches, combination of detectors

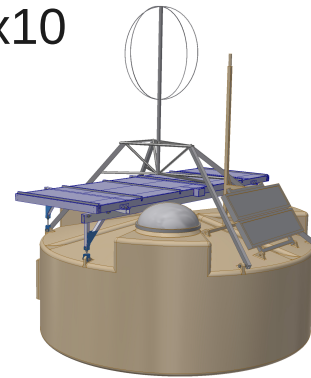
event-wise **reconstruction of $X_{\max}$**

- ♦ first SD-based mass estimator competitive to FD, raise in statistics by x10
- ♦ performance validated on simulations and data (hybrid calibration)
- ♦ first measurement of $\sigma(X_{\max})$ beyond 80 EeV → low proton fraction!

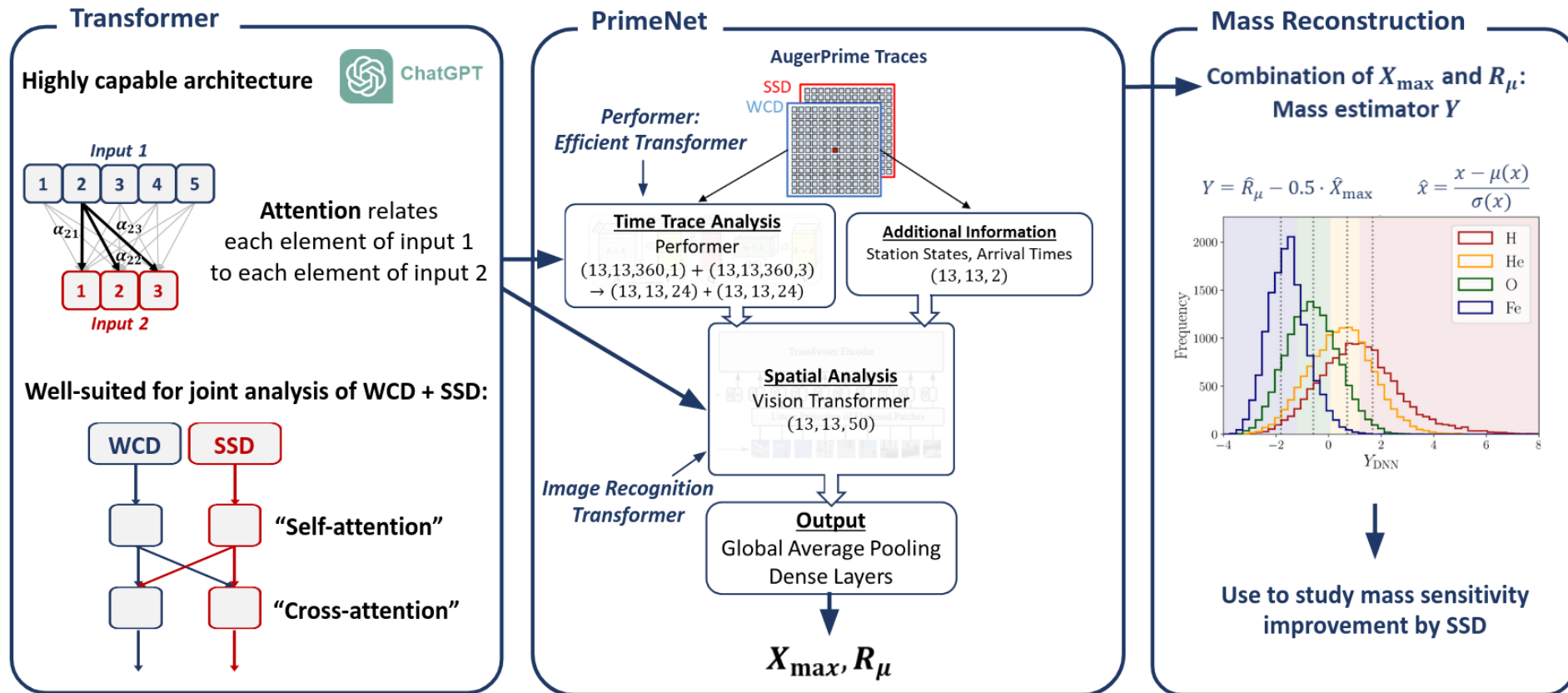
AugerPrime Upgrade will enable additional insights and cross checks!

E.g.: reconstructing muonic component, improved energy estimator, etc.

Muon number strongly depends on interaction models → refinement of simulations

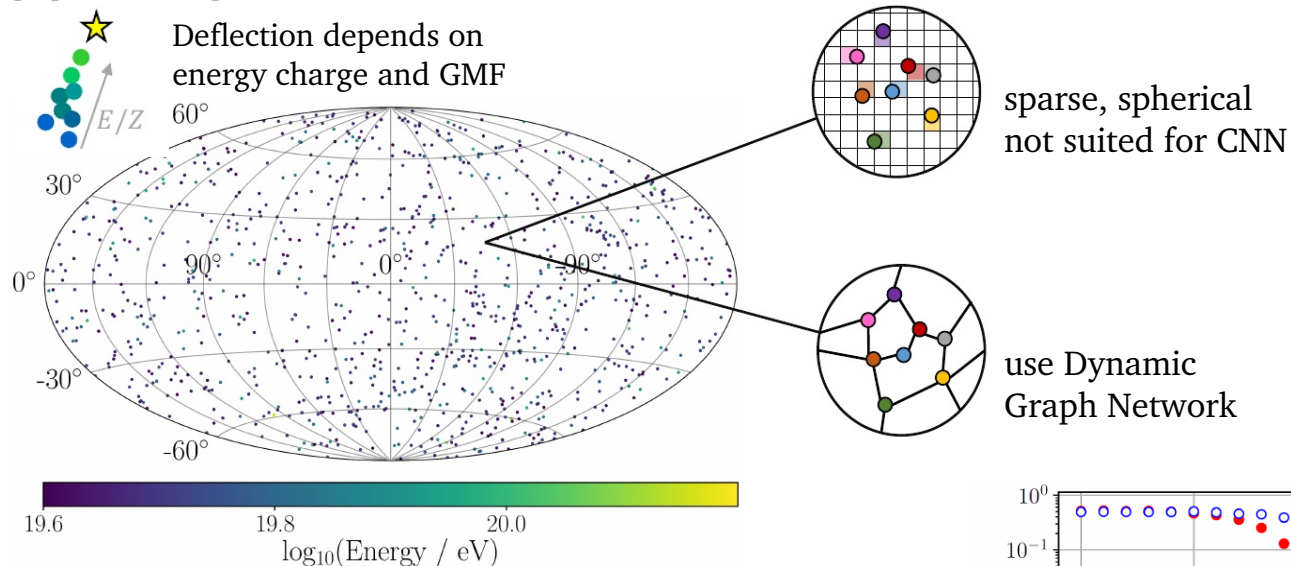


PrimeNet - Transformer-Based Neural Network Architecture for AugerPrime



Search for UHECR Origins

graphics: N. Langner



One measured sky (spherical)

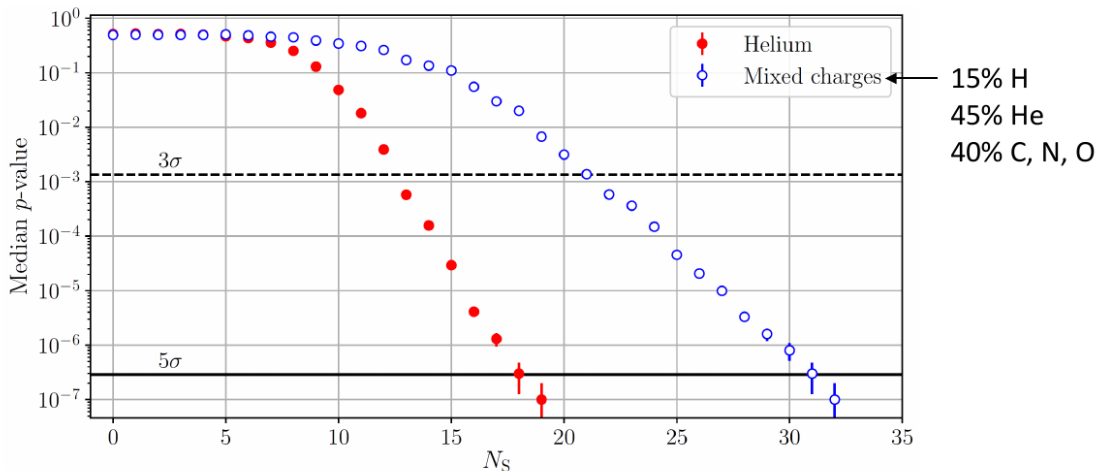
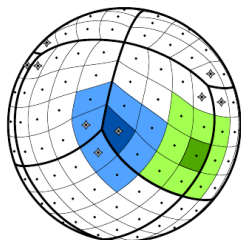
Learn to classify between

- isotropic sky / signal
- use dynamic edge convolutions

Continuously distributed on **sphere**

Hybrid approach:
'Indexed Conv'
Define 'HEALPix filters'

O. Kalashev et al.,
10.1088/1475-7516/2020/11/005
N. Krachmalnicoff et al., A&A 628, A129 (2019)



Generalization Capacities on Data

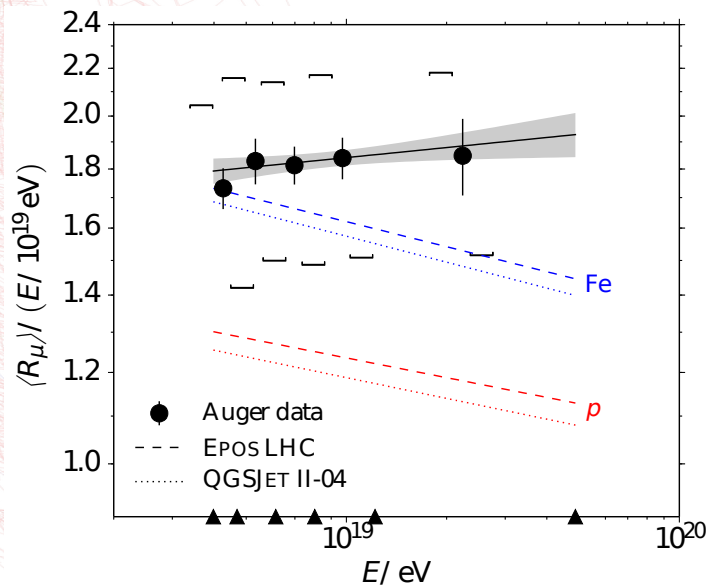
DNNs and Domain Adaption

- models are trained using physics simulations
- trained models are applied to data
 - can lead to reconstruction biases



Domain Adaption

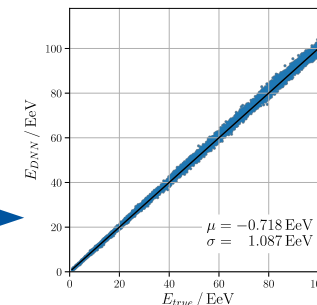
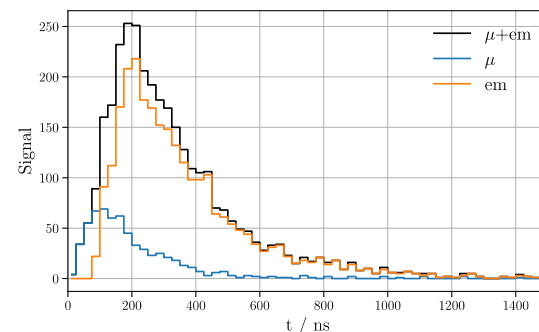
- model trained on simulation but applied on data
- observation of muon excess in measured air-shower data
- can lead to reconstruction bias



Simulation

70% electromagnetic

30% muonic

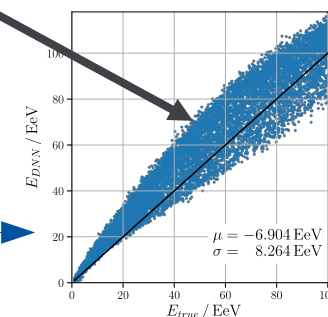
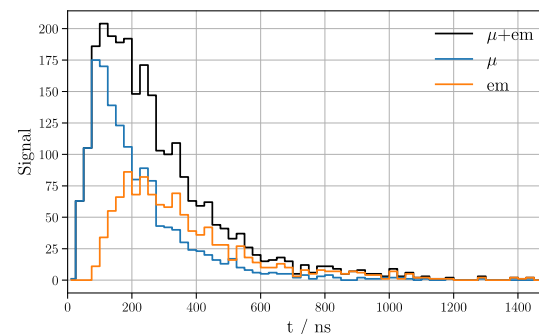


Network can not handle modified traces

'Data'

30% electromagnetic

70% muonic



Simulation Refinement

Erdmann et al.
Comput Softw Big Sci (2018) 2: 4

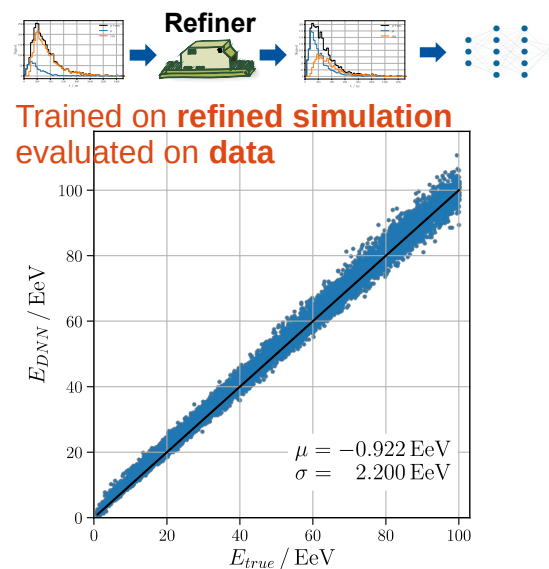
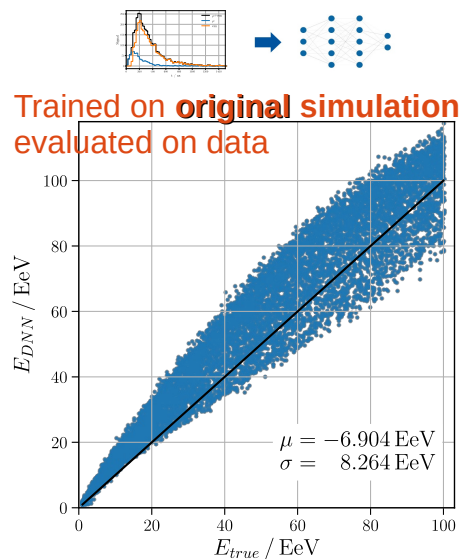
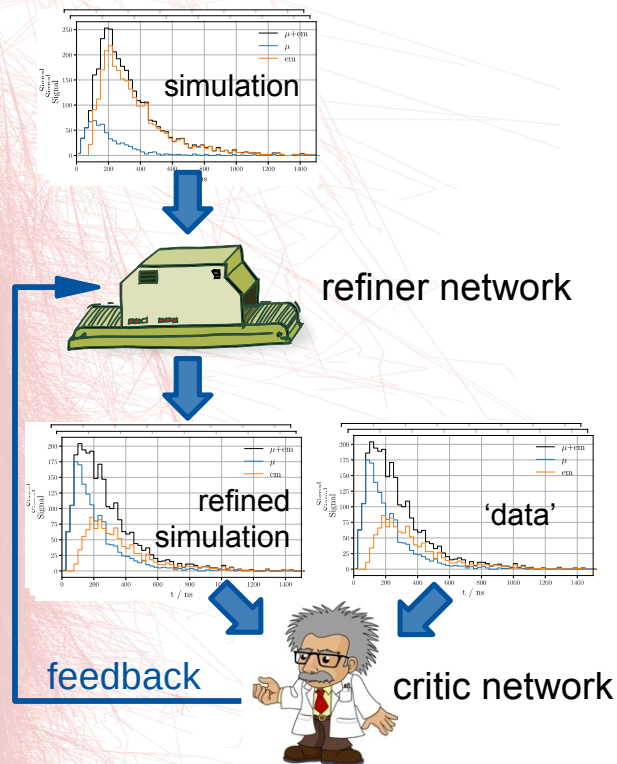


ERLANGEN CENTRE
FOR ASTROPARTICLE
PHYSICS



mitigate data / simulation mismatches → train *refiner* to refine simulated data

- feedback given by adversarial *critic* network, rating the refined simulation quality
 - refiner uses feedback to improve performance
- improved performance when training with refined simulation



Summary



ERLANGEN CENTRE
FOR ASTROPARTICLE
PHYSICS



Deep learning is game changer → analyze signal traces (exploit correlations in n-D data)

Deep Learning at the Pierre Auger Observatory:

- extract mass-sensitive information, improved event reconstruction
- refinement of simulations, arrival direction searches, combination of detectors

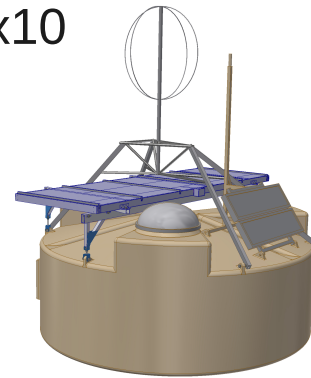
event-wise **reconstruction of $X_{\max}$**

- ♦ first SD-based mass estimator competitive to FD, raise in statistics by x10
- ♦ performance validated on simulations and data (hybrid calibration)
- ♦ first measurement of $\sigma(X_{\max})$ beyond 80 EeV → low proton fraction!

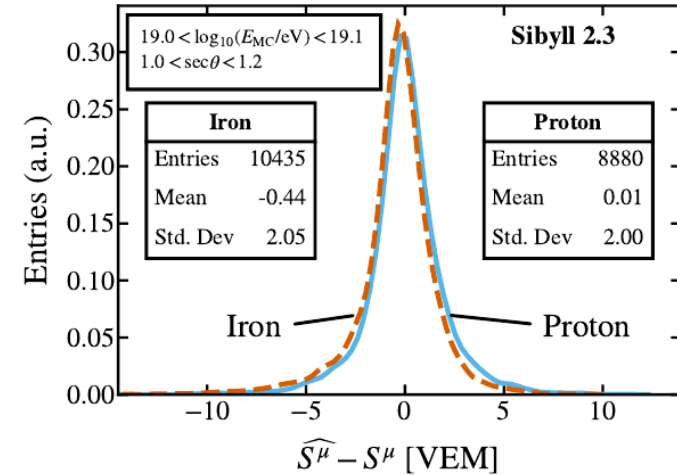
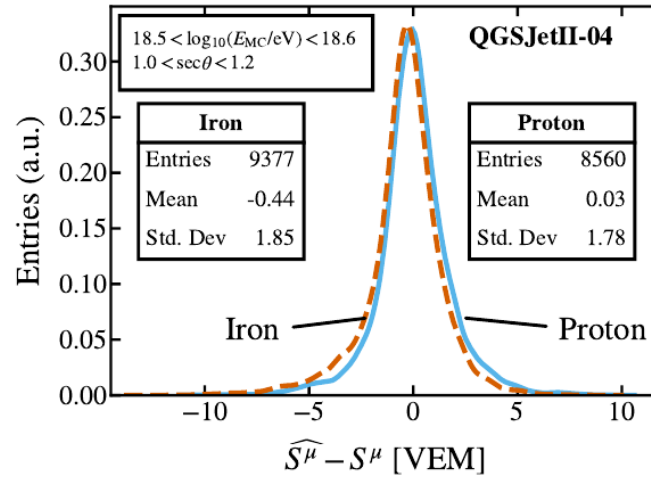
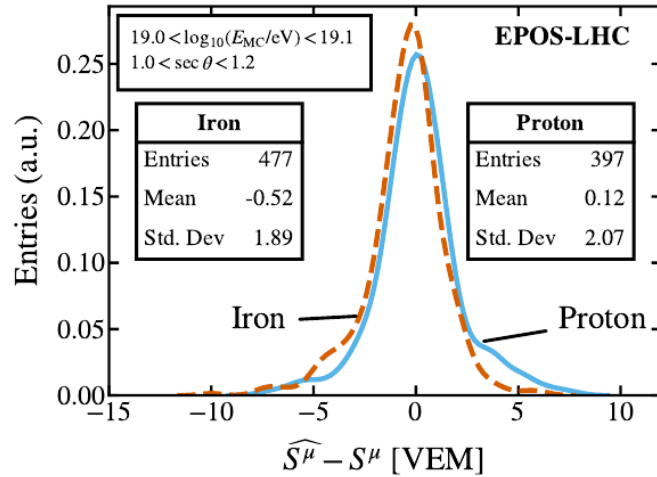
AugerPrime Upgrade will enable additional insights and cross checks!

E.g.: reconstructing muonic component, improved energy estimator, etc.

Muon number strongly depends on interaction models → refinement of simulations



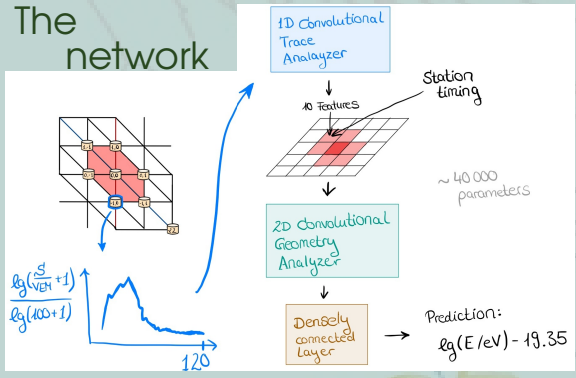
Dependency on hadronic model



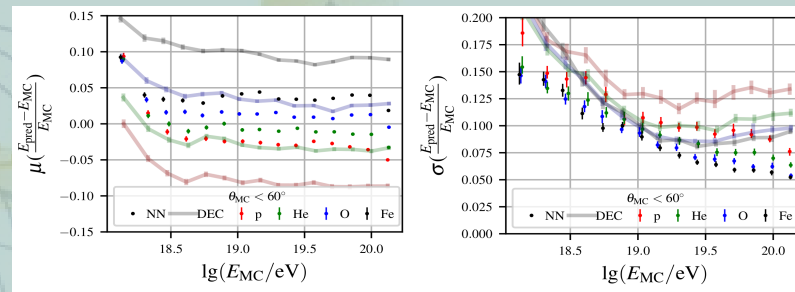
- RNN trained using EPOS-LHC
- validate using other hadronic interaction models
 - each model features different muon content
- RNN shows no strong dependency on the interaction model

Deep-Learning based Estimation of the Ultra-High Energy Cosmic Ray Spectrum using the Surface Detector of the Pierre Auger Observatory

The network

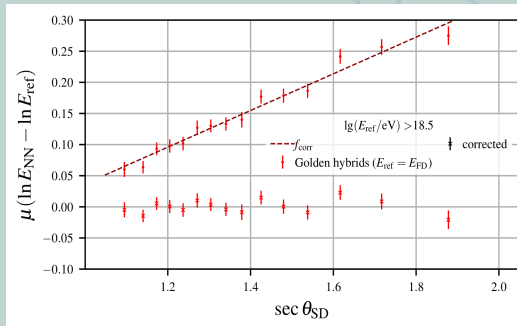


MC test data set

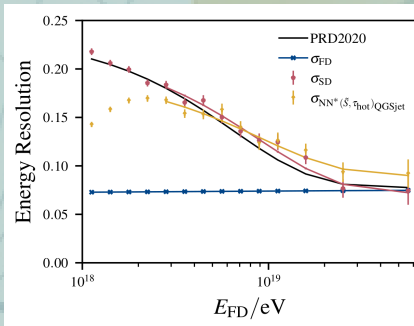


→ Composition dependent bias is reduced

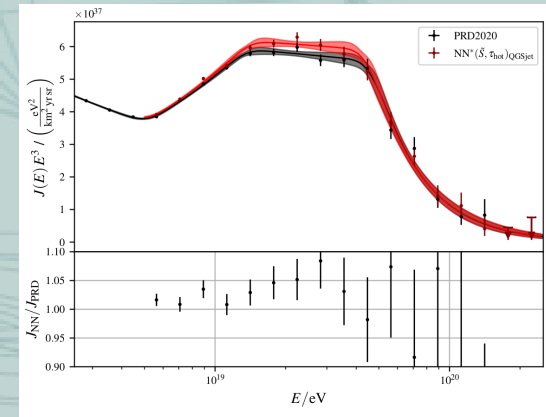
Bias correction using Golden Hybrid events



→ after correction the resolution is comparable to the standard reconstruction

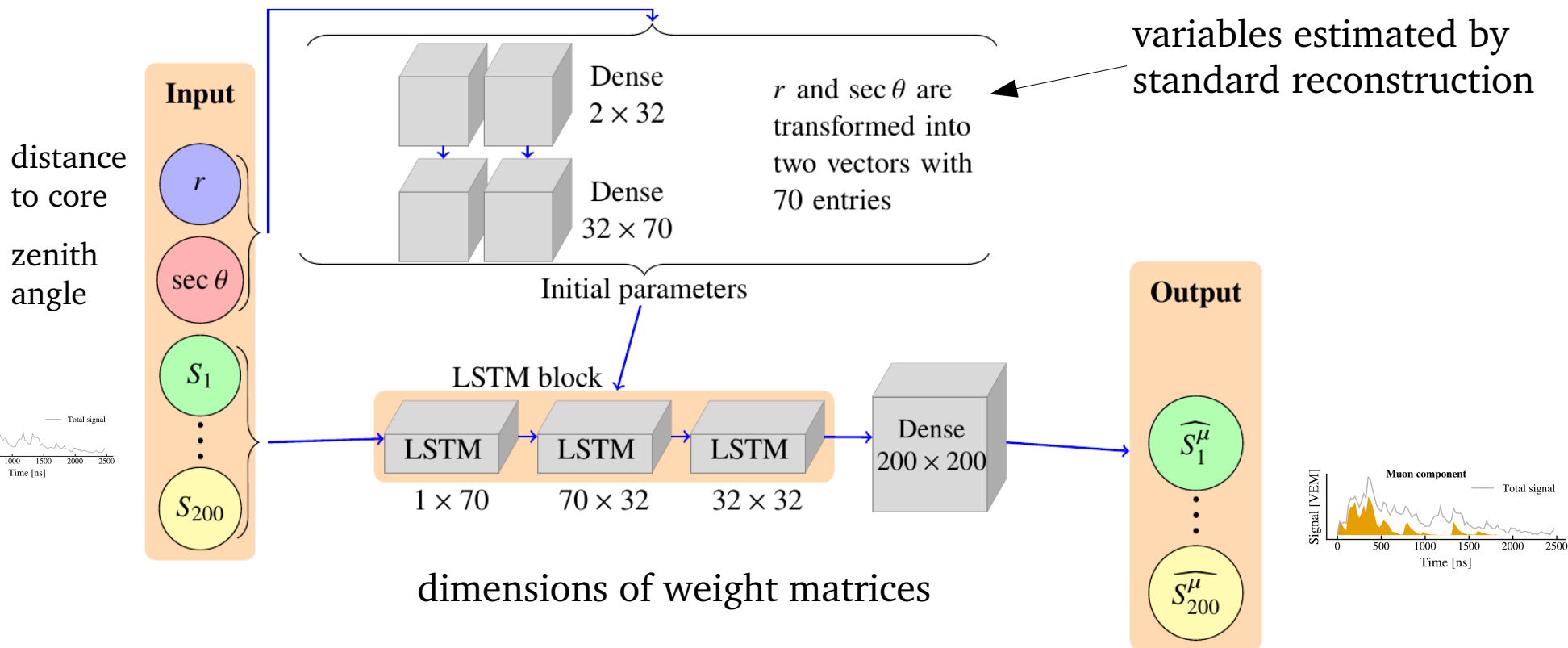


The unfolded energy spectrum



RNN architecture

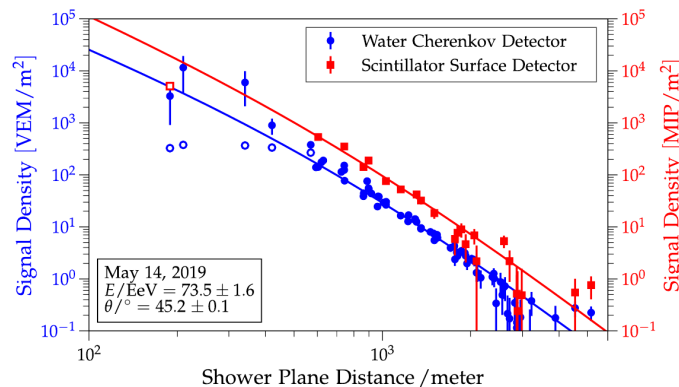
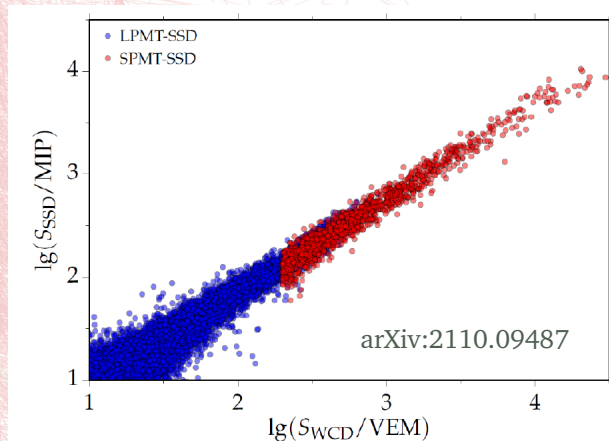
- station-wise application of RNN



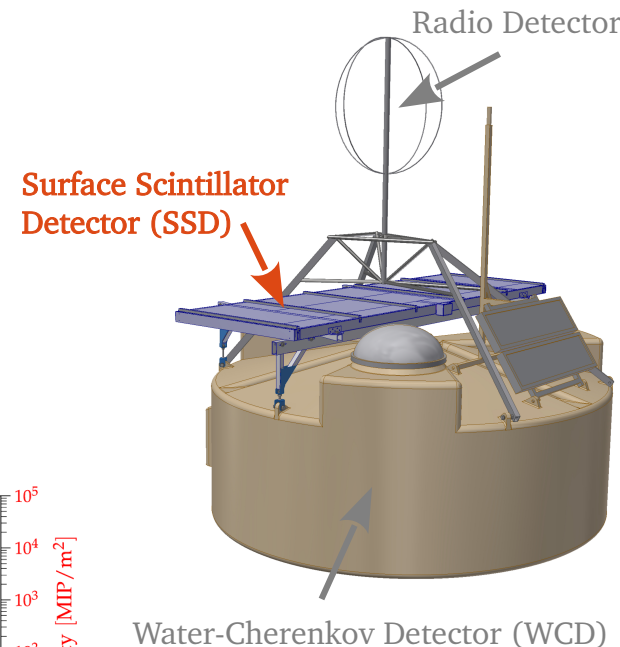
Surface Scintillator Detector

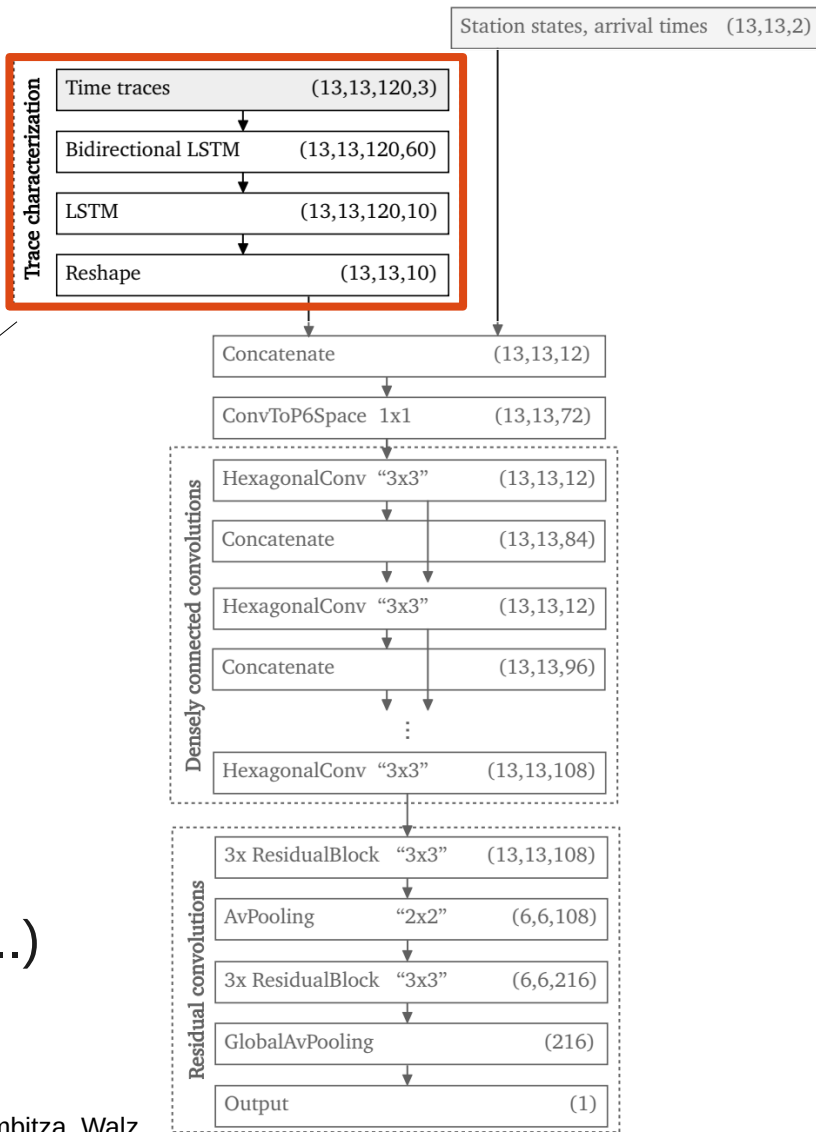
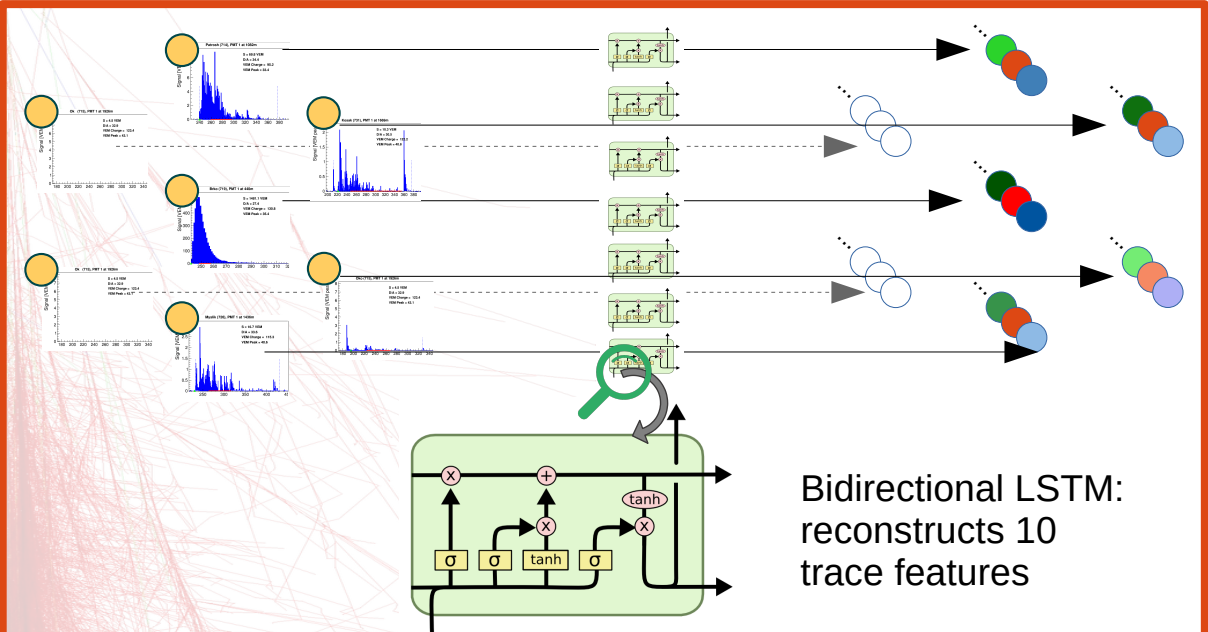
Upgrade each WCD with plastic scintillator

- Efficient for vertical showers ($<60^\circ$)
- Especially sensitive to electromagnetic component
 - ◆ Mass composition studies
 - ◆ Improved energy reconstruction (composition bias)
 - ◆ Improved photon searches

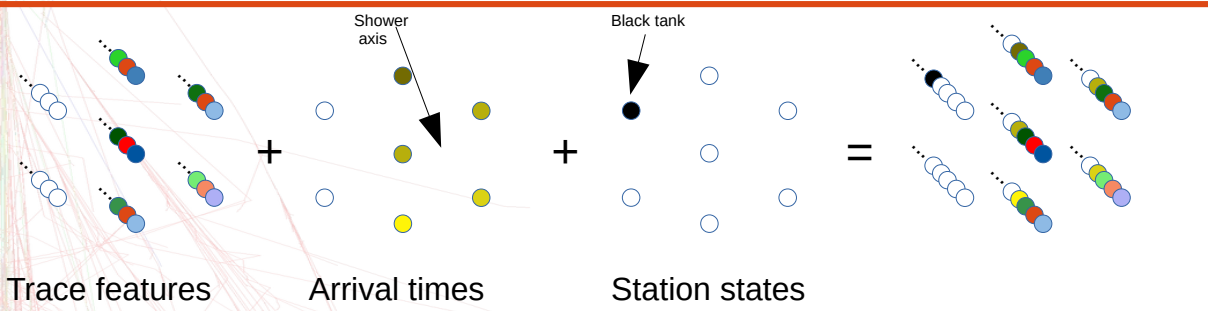


<https://pos.sissa.it/395/218>

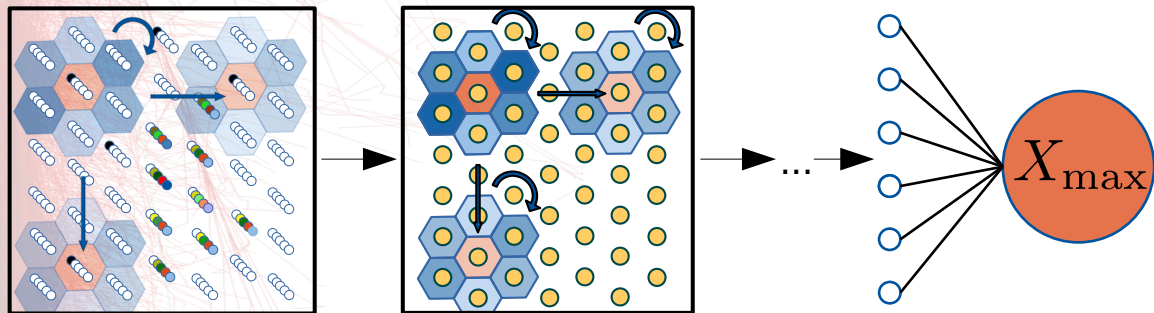




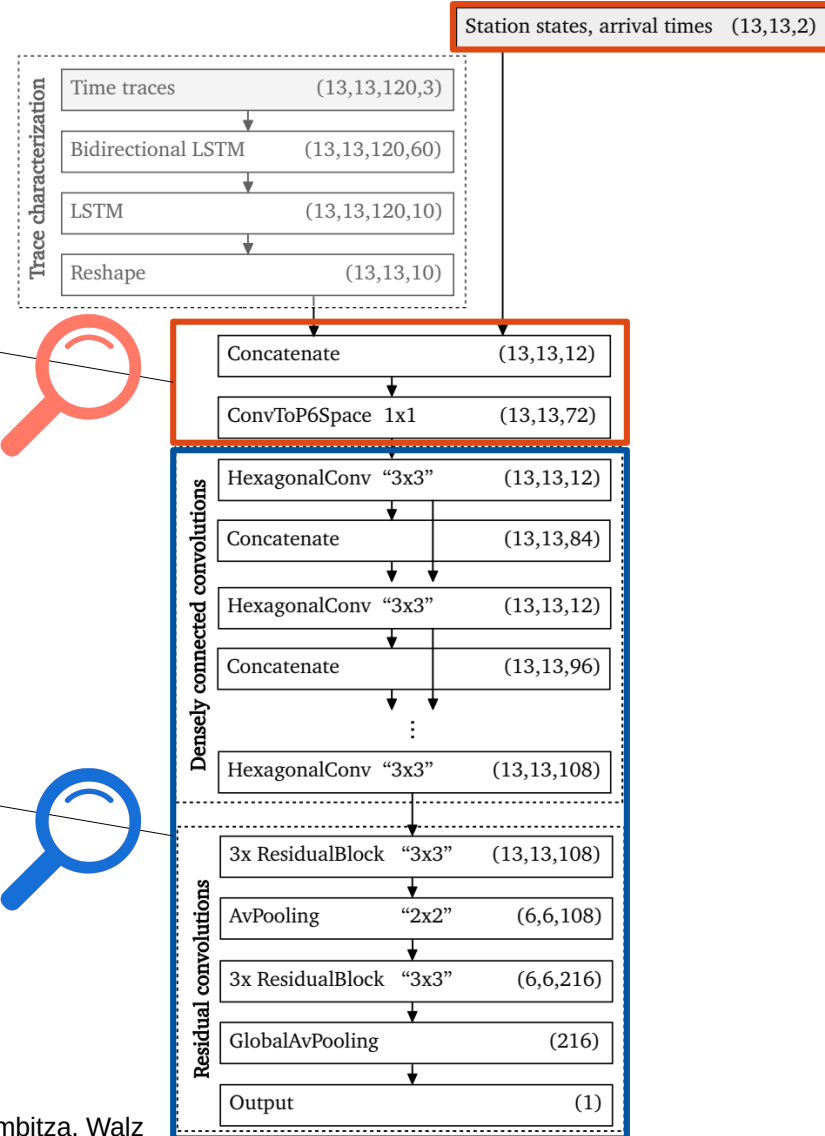
- # RNN part extracts trace features
- **same network** (same weights) for each station
 - same kind of features (same color) per station (features e.g.: rising edge, falling edge, peaks ...)
 - but different characteristic → different strength



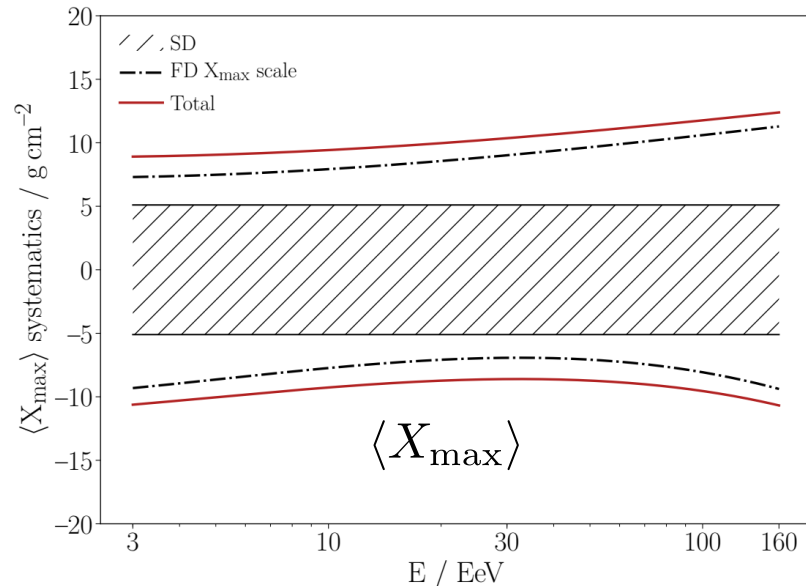
- add station states and arrival times to trace features



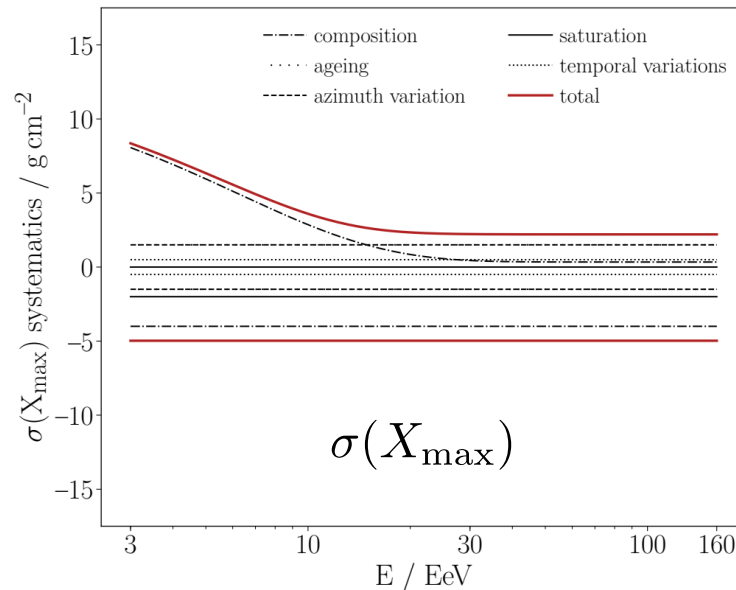
- hexagonal convolutions to combine features in space and time (DenseNet, ResNet)
- finally predict single $X_{\max}$ value



Expected Systematics



- method calibrated using the FD
 - sys. uncertainty 10 – 15 g/cm^2
- uncertainty similar to delta method



- no calibration using FD
 - sys. uncertainty 5 – 10 g/cm^2
 - way smaller than fluctuations
- **1st measurement beyond 80 EeV**
- **provide new insights in composition**

Energy-Dependent Composition Bias

Composition biases of the measurement

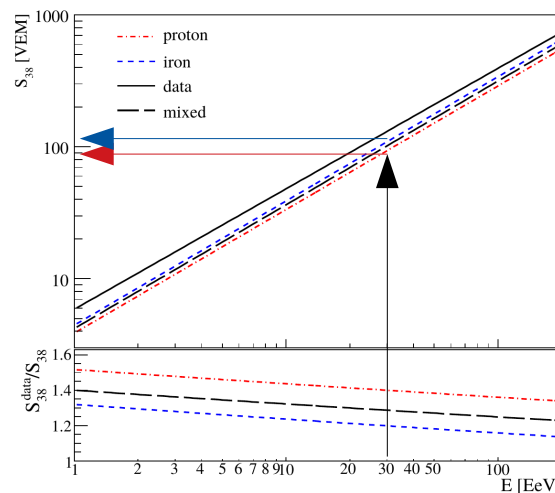
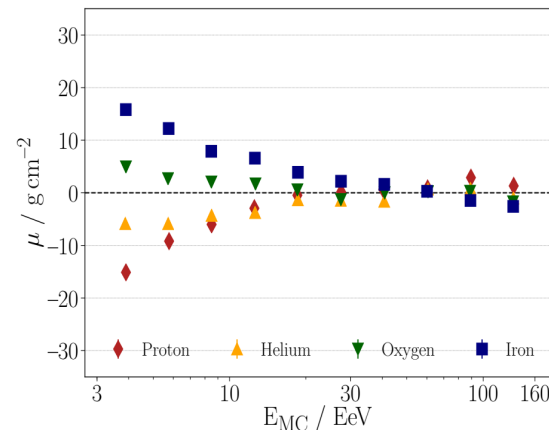
DNN reconstruction

- Maximal for pure proton / pure iron
- Minimal 50:50 mixture proton / iron

SD energy reconstruction

- S38 bias depends on composition + spectrum
 - ♦ Minimal for pure compositions
 - ♦ Maximal for 50:50 mixture proton / iron

→ simulation study to quantify systematic uncertainty



Training

- training using 390,000 EPOS-LHC events
- 90,000 adaptive parameters
- implemented in PyTorch
- training on GPU takes 8 hours

